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A MACROTERRAIN LANDTYPE ASSOCIATION  
CLASSIFICATION MODEL FOR  
THE GREAT BASIN

by

Frank L. Dougher

A thesis submitted in partial fulfillment  
of the requirements for the degree

of

MASTER OF SCIENCE

in

Geography

Approved:

Utah State University  
Logan, Utah

2002

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## ABSTRACT

### A Macroterrain Landtype Association Classification Model For The Great Basin

by

Frank L. Dougher, Master of Science

Utah State University, 2002

Major Professor: R. Douglas Ramsey  
Department: Geography and Earth Resources

Three Macroterrain Landtype Association classification models were developed to stratify and categorize Utah's West Desert. These models approached terrain segmentation using an energy-flow paradigm from erosional to transitional to depositional landscapes. One model was developed as a slope-based deterministic model that used slope-threshold limits to discriminate between Landtype Associations. A second model was developed as a stochastic, training-data driven supervised classification, using comparative *t*-values to classify the landscape to the most similar landtype class. The third model was a probabilistic algorithm, which classified the landscape to the most probable class based on multiple iterations of the stochastic model. These models were assessed for performance against Macroterrain Landtype Association classifications from three independent geographical datasets. The performance assessment involved calculating model-to-reference agreement, a piecewise assessment of errors for each



Macroterrain Landtype Association class, and a measure of the model-to-reference performance relative to that performance expected from random chance.

(110 pages)

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## INTRODUCTION

Beginning in 1994, the College of Natural Resources (CNR) at Utah State University (USU) participated in a five-year study of the threatened, endangered and sensitive (TES) species existing within the Hill Air Force Base (HAFB) Military Operations Area (MOA). The HAFB TES Project was a cooperative program between USU, the Department of Defense (DOD), the Bureau of Land Management (BLM), the Utah Division of Wildlife Resources, and the Jack Berryman Institute (Sharik *et al.*, 2000). The scope of this study included terrestrial and aquatic invertebrates, mammals, reptiles, birds, and plants. As most of these data were point-based, an ecological classification system was developed as an interpolation and extrapolation tool. The Ecological Classification and Mapping (ECM) system is a modification of the existing ECOMAP structure developed by the US Forest Service (West *et al.*, in press).

ECOMAP, as described by McNab and Ayers (1994), is a United States Department of Agriculture (USDA) Forest Service (USFS) framework for stratifying the landscape into hierarchically smaller units of increasing ecological uniformity. At its upper (coarser) levels, it follows Bailey's Ecoregions classification system, and is intended to "[provide] field units with an essential tool and scientific basis to plan for and implement ecosystem management" (McNab and Ayers, 1994). Bailey's original classification (Table 1) divides the Earth into *Domains* (Figure 1), *Divisions* (Figure 2), and *Provinces* (Figure 3), based on "regional variations in climate, vegetation, and soil" (Bailey and Hogg, 1986).

Table I. Explanation of portion of Ecoregions Map of North America (taken from Bailey and Hogg, 1986).

<i>Lowland ecoregions</i>	<i>Highland ecoregions*</i>
<b>100 Polar Domain</b>	
120 TUNDRA DIVISION	H120 TUNDRA REGIME HIGHLANDS
121 Low-arctic Tundra Province	M121 Brooks Range Province
122 High-arctic Tundra Province	M122 Northeast Seaboard Mts. Province
130 SUBARTIC DIVISION	H130 SUBARTIC REGIME HIGHLANDS
131 Subarctic Parkland Province	M131 Alaska Range Province
133 Boreal Forest Province	M132 Subarctic Rockies Province
	P133 Yukon-Sitkine Plateau Province
<b>200 Humid Temperate Domain</b>	
210 HUMID WARM-SUMMER CONTINENTAL DIVISION	H210 HUMID WARM-SUMMER CONTINENTAL REGIME HIGHLANDS
211 Laurentian Mixed Forest Province	M211 Columbia Forest Province
	P212 Fraser-Nechako Plateau Province
220 HUMID HOT-SUMMER CONTINENTAL DIVISION	
221 Eastern Deciduous Forest Province	
230 HUMID SUBTROPICAL DIVISION	
231 Outer Coastal-plain Forest Province	
232 Southeastern Mixed Forest Province	
240 HUMID MARITIME DIVISION	H240 HUMID MARITIME REGIME HIGHLANDS
241 Willamette-Puget Forest Province	M240 Pacific Forest Province
250 SUBHUMID PRAIRIE DIVISION	
251 Prairie Parkland Province	
252 Prairie Brushland Province	
253 Tall-grass Prairie Province	
254 Aspen Parkland Province	
260 MEDITERRANEAN DIVISION	H260 MEDITERRANEAN REGIME HIGHLANDS
261 California Grassland Province (Central Valley)	M261 Sierran Forest Province
	M262 Californian Chaparral Province
<b>300 Dry Domain</b>	
310 SEMI-ARID STEPPE DIVISION	H310 SEMI-ARID STEPPE REGIME HIGHLANDS
311 Great Plains Shortgrass Prairie Province	M311 Rocky Mountain Forest Province
312 Palouse Grassland Province	M312 Upper Gila Mts. Forest Province
313 Intermountain Sagebrush Province	M315 Sierra Madre Occidental Province
314 Mexican Highlands Shrub Steppe Province	M316 Sierra Madre Oriental Province
315 Sinaloa Coast Province	P313 Colorado Plateau Province
316 Rio Grande Shrub Steppe Province	A314 Wyoming Basin Province
320 ARID DESERT DIVISION	H320 ARID DESERT REGIME HIGHLANDS
321 Chihuahuan Desert	M321 Baja California Province
322 American Desert Province (Mojave-Colorado-Sonoran)	
<b>400 Humid Tropical Domain</b>	
410 TROPICAL SAVANNA DIVISION	H410 TROPICAL SAVANNA REGIME HIGHLANDS
411 Everglades Province	M412 Sierra Madre del Sur Province
414 Campeche-Yucatan Savanna Province	A413 Central Mexico Province
415 Pacific Savanna Woodland Province	
420 TROPICAL RAIN-FOREST DIVISION	H420 TROPICAL RAIN-FOREST REGIME HIGHLANDS
421 Caribbean Coast Rain-forest Province	M421 Central American Ranges Province

\* Key to letter symbols: H=Highlands; M=Mountains; P=Plateau; A=Altitude

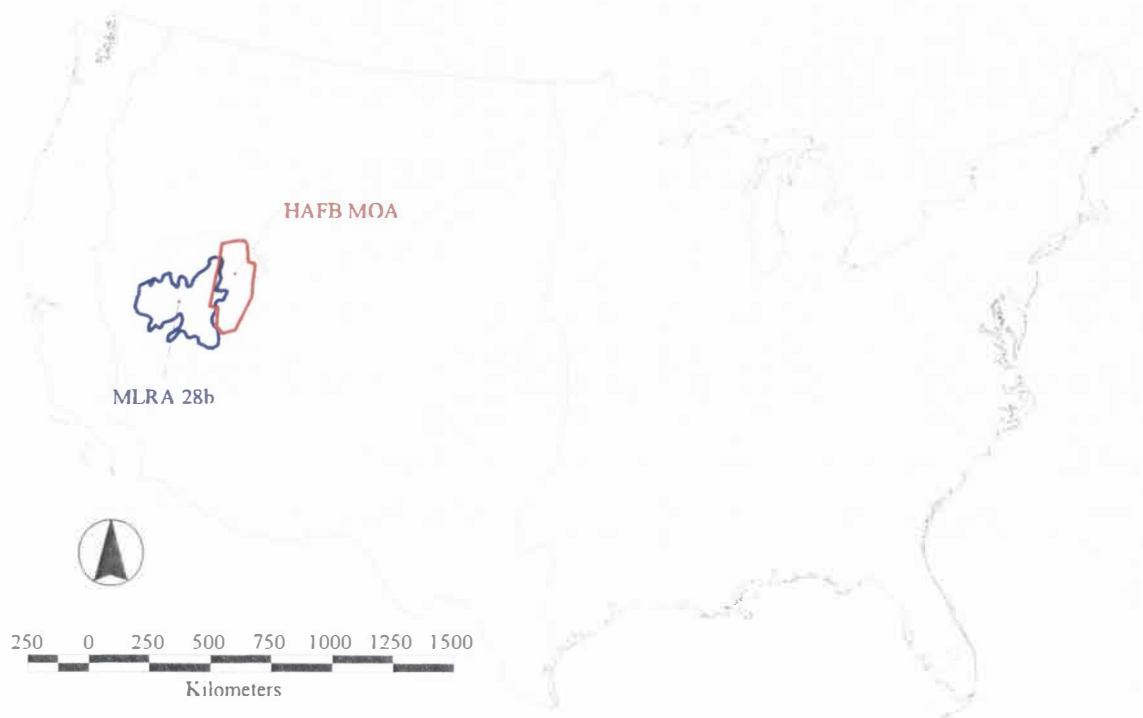


Figure 1. ECOMAP Domains and boundaries for HAFB MOA and MLRA 28b.



Figure 2. ECOMAP Divisions and boundaries for HAFB MOA and MLRA 28b.



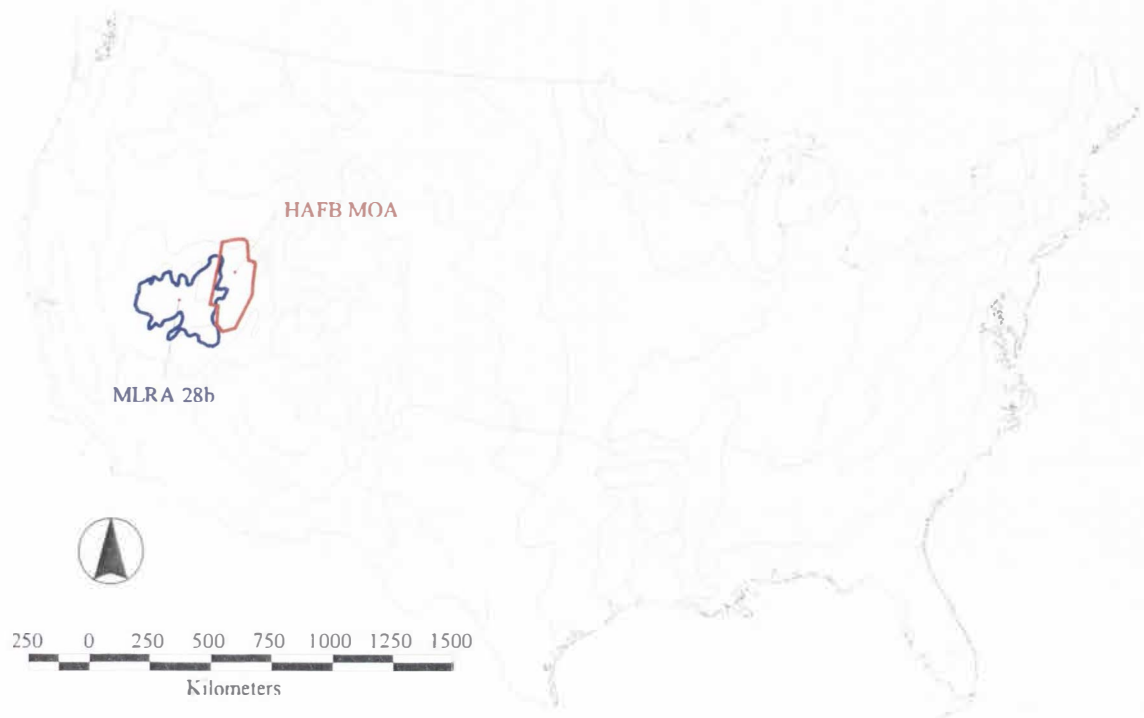


Figure 3. ECOMAP Provinces and boundaries for HAFB MOA and MLRA 28b.



Figure 4. ECOMAP Sections and boundaries for the HAFB MOA and MLRA 28b.

ECOMAP continued this system by further subdividing Bailey's *Provinces* into Sections (Figure 4), based on locally dominant geologic materials and landforms (West *et al.*, in press). Furthermore, ECOMAP provided guidelines for four additional ecological subdivisions, in order of coarsest to finest: *Subsections*, *Landtype Associations*, *Landtypes*, and *Landtype Phases* (McNab and Ayers, 1994). These levels, though loosely defined in scale and criteria, are left up to local entities to define and delineate both for the sake of mapping efficiency and to allow local environmental factors, priorities, and needs to dictate unit delineation. The end result is an eight-level hierarchical classification (**Table II**) system, which could divide ecological systems from continental scales down to parcels less than 10 acres (McNab and Ayers, 1994).

The ECM group of the HAFB TES Project adopted the basic ECOMAP framework, but modified the unit nomenclature, scales, and criteria of the four finest orders of the classification to better suit Great Basin ecosystems, and expanded the ECOMAP framework by adding two additional levels of classification that would exist outside the higher-order framework. It was also determined that, as a modification to the ECOMAP ordering system, each progressively finer layer of the four locally delineated orders would be delineated from the next higher order by a single determining factor (West *et al.*, in press) wherever this was possible. Thus, Bolson Segments [ECOMAP Subsections] (Figure 5) were delineated from ECOMAP *Sections* by hydrologic drainage. *Macroterrain Units* [Landtype Associations] (Figure 6) were to be delineated from *Bolsons* by a classification of landform type; i.e. Mountain Massif, Bajada, or Valley Bottom. *Mesoterain Units* [Landtypes] (Figure 7) were subdivided from *Macroterrain*

Table II. Principal map unit design criteria of ecological units (taken from West *et al.*, in press).

ECOLOGICAL UNIT	PRINCIPAL MAP UNIT DESIGN CRITERIA
Domain	Broad climatic zones or groups (e.g. dry, humid, tropical).
Division	Regional climatic types (Koppen, 1931; Trewartha, 1968). Vegetation affinities (e.g. prairie or forest). Soil order.
Province	Dominant potential natural vegetation (Kuchler, 1964). Highlands or mountains with complex vertical climate-vegetation-soil zonation.
Section	Geomorphic province, geologic age, stratigraphy, lithology. Regional climatic data. Phases of soil orders, suborders, or great groups. Potential natural vegetation. Potential natural communities (PNC).
Subsection	Geomorphic processes, surficial geology, lithology. Phases of soil orders, suborders, or great groups. Subregional climatic data. PNC-formation or series.
Landtype Association	Geomorphic processes, geologic formation, surficial geology and elevation. Phases or soil subgroups, families, or series. Local climate. PNC-series, subseries, plant associations.
Landtype	Landform and topography (elevation, aspect, slope gradient and position). Phases of soil subgroups, families, or series. Rock type, geomorphic processes. PNC-plant associations.
Landtype Phase	Phases of soil families or series. Landform and slope position. PNC-plant associations or phases.

*Units* by surficial soil or geology classification. Lastly, *Microterrain Units* [Landtype Phases] (Figure 8) were subdivided from *Mesoterrain Units* by slope position (*i.e.* ridge, side slope, or foot slope and channel bottom) wherever topography allowed such delineation. Furthermore, two more levels, *Ecological Sites* and *Vegetation Stands*,

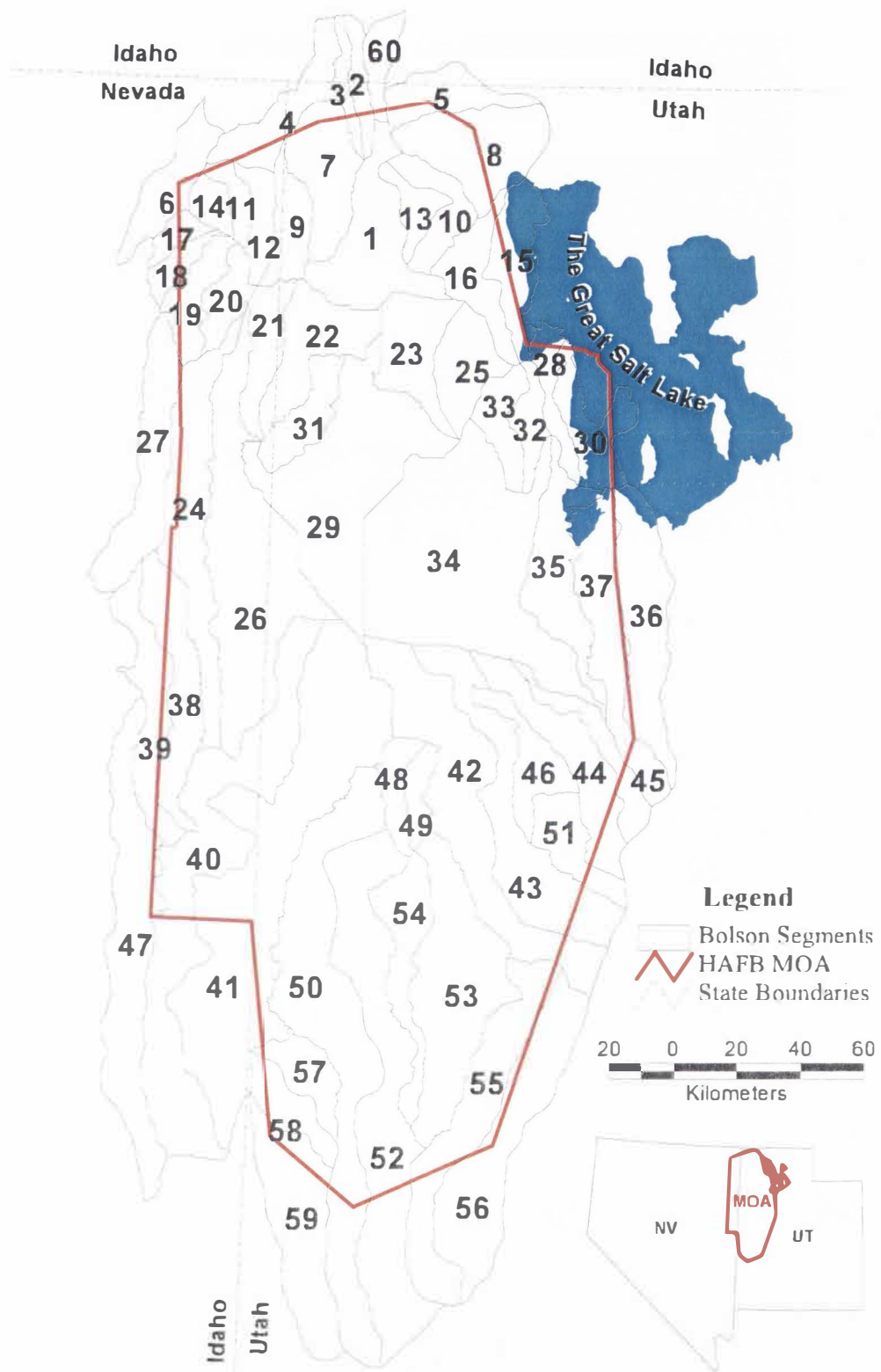


Figure 5. Bolson Segments for Utah's West Desert and HAFB MOA.

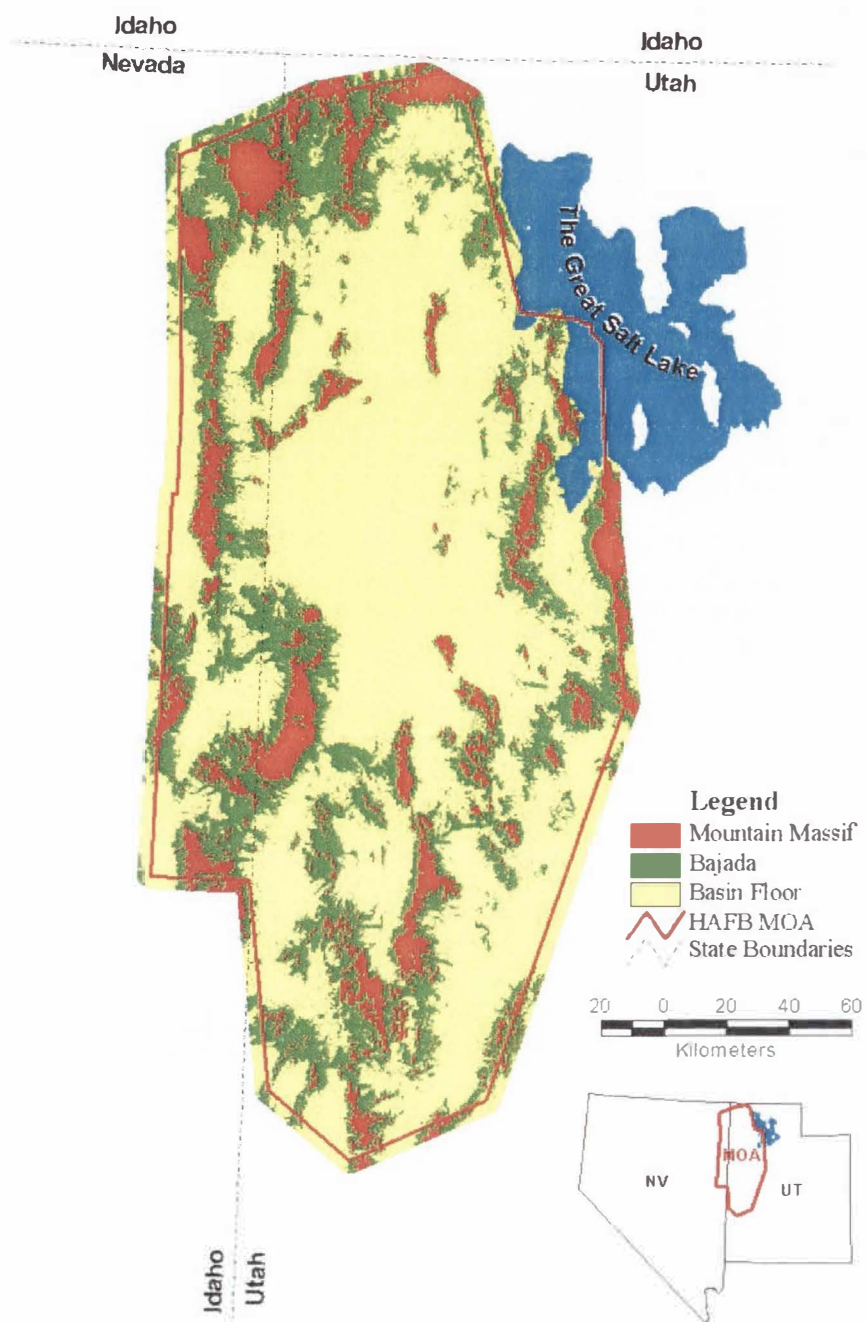


Figure 6. Macroterrain Units for the Hill Air Force Base MOA.



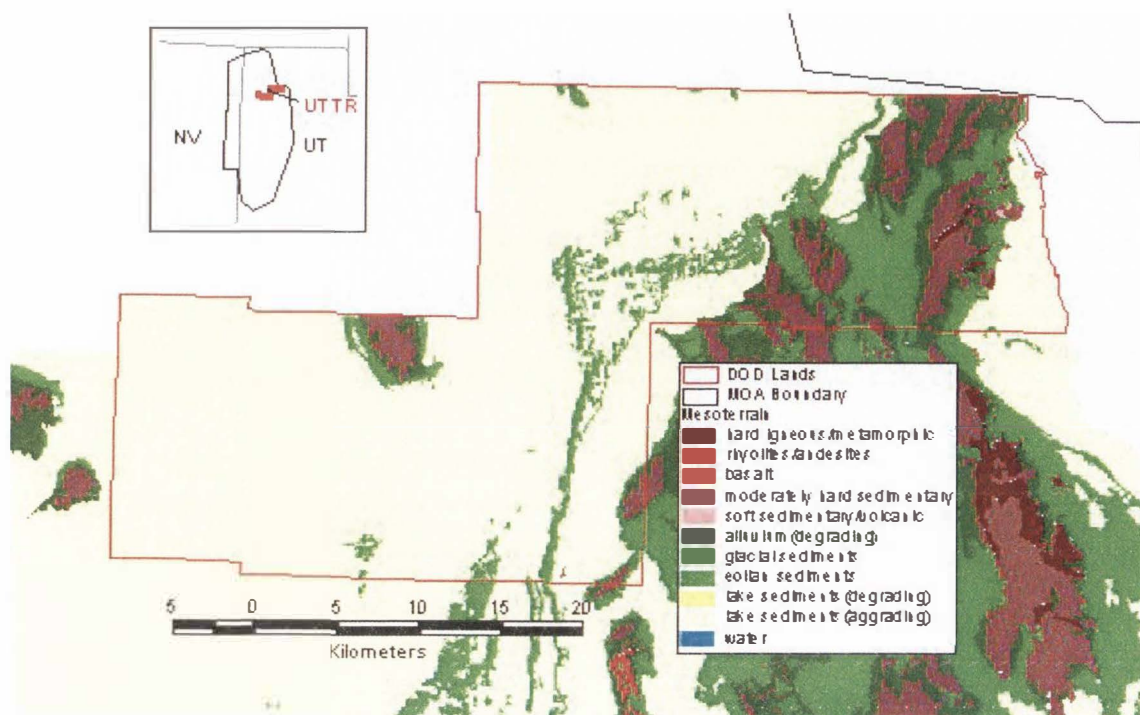


Figure 7. Mesoterrain Units for the Utah Test and Training Range.

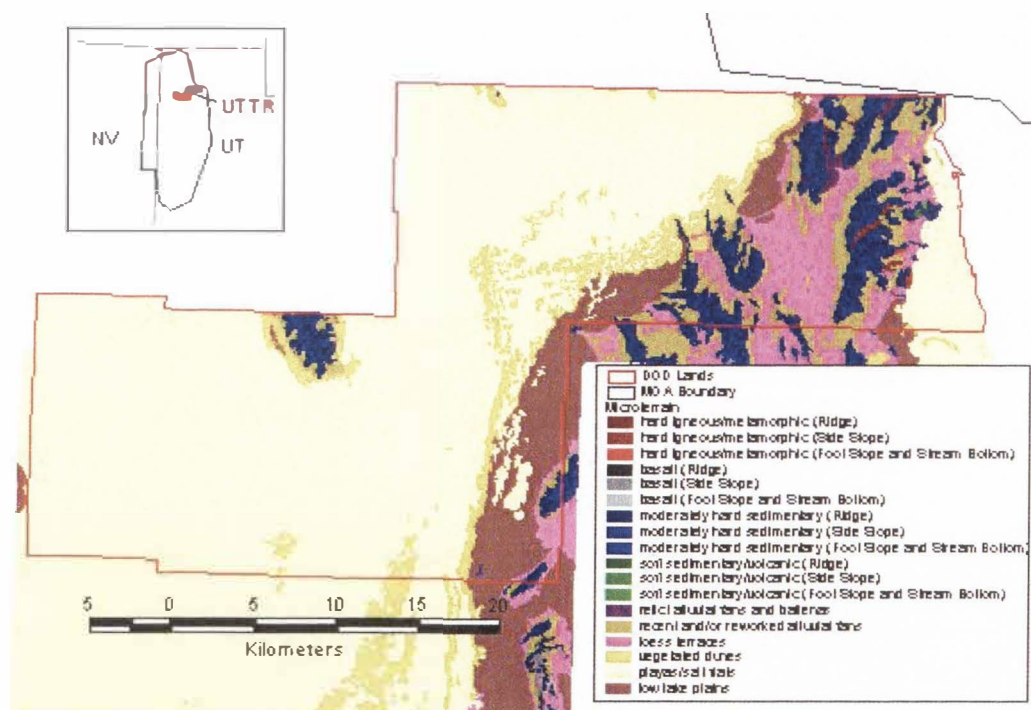


Figure 8. Microterrain Units for the Utah Test and Training Range.

were added to the bottom of the ECM hierarchy, and were delineated independently from the higher orders by soil survey data and by *in situ* classification, respectively (West *et al.*, in press).

The delineation of the fifth level of the ECM classification, Macroterrain Units (Table II), required the development of a system for classifying landforms from digital elevation models (DEMs). During the execution of the ECM section of the HAFB TES Project, three raster-based models were developed to classify the landscape of the HAFB MOA into the requisite three classes (Figure 6). Significant differences between the models were noted (Figure 9), but never analyzed. It was determined that further study should assess the agreement of each model with independent geographic information with the aim of determining which classification method is most effective for the Great Basin. This assessment is the focus of this study.

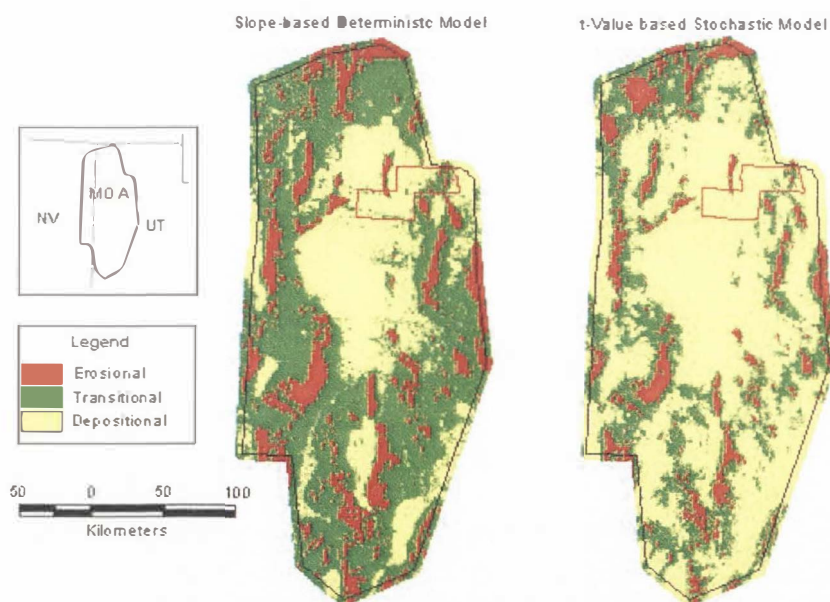


Figure 9. Sample outputs from HAFB ECM Macroterrain Landtype Association Classification.

## PROJECT OBJECTIVES

The primary objective of this study was to generate a Macroterrain Unit landtype classification of the Hill Air Force Base Military Operations Area applicable to the framework of the U.S. Forest Service's ECOMAP ecological classification system, and to assess the various methods used in the production of this classification. As a part of a larger ecological classification model being developed by West *et al.* (in press), the methods developed in this study should be applicable throughout the Great Basin. Furthermore, this study aims to improve our understanding of the use of spatial models in the classification of topographic landforms and the delineation of topographically dependant ecological communities.

The specific goals of this study are to:

- 1) Develop a topography-based model for the separation of a Great Basin landscape into discrete Macroterrain Units.
- 2) Develop a supervised classification model to characterize topographic data from a Great Basin landscape into discrete Macroterrain Units.
- 3) Assess the agreement of the output of these spatial models with independently derived geographic data.



## STUDY AREAS

### *Hill Air Force Base, Military Operations Area*

Located in predominately in northwestern Utah, and to a lesser extent in northeastern Nevada, the Hill Air Force Base (HAFB) Military Operations Area (MOA) covers an area of 4.5 million hectares (17,400 mi<sup>2</sup>) of what is known in Utah as the West Desert (Figure 10). The airspace over this area, is restricted for and administered by the Department of Defense (DOD) for the training of personnel and testing of military

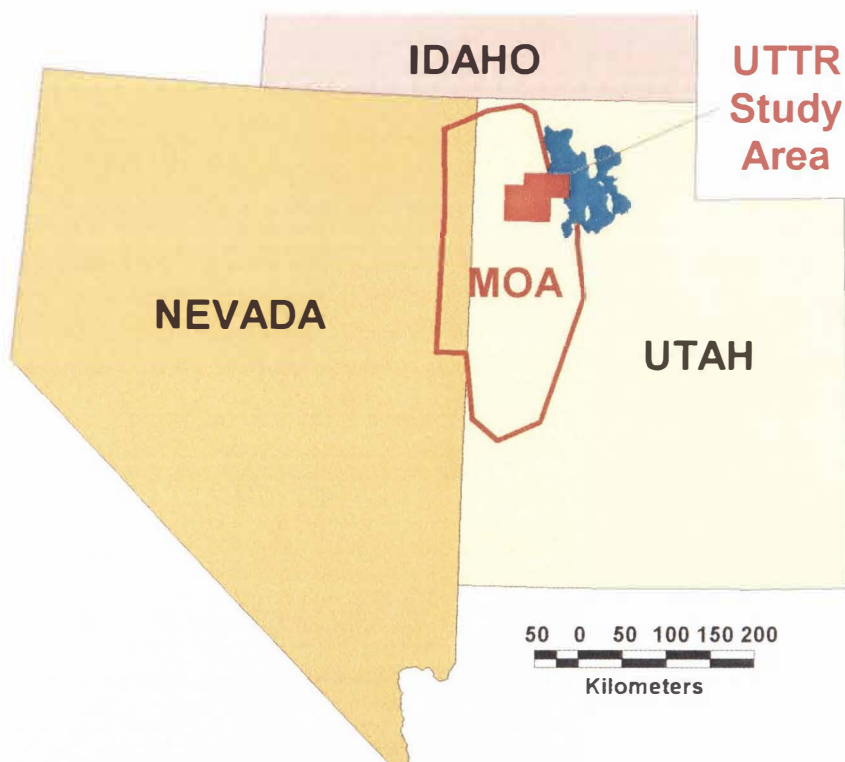


Figure 10. Location of the HAFB Military Operations Area (MOA) and the Utah Test & Training Range (UTTR).

materiel (Sharik *et al.*, 2000). Within the MOA, also referred to as the Range Complex (Tilton, 1998), are two land parcels owned and administered by HAFB. The northernmost of these parcels, the Utah Test and Training Range (UTTR) North Range or “Eagle Range” (Sharik *et al.*, 2000), covers 147,000 ha (566 mi<sup>2</sup>), and is the primary focus area for this study. The southernmost UTTR area is the South Unit or “Wendover Range,” and covers some 230,000 ha (890 mi<sup>2</sup>), this area will be the secondary focus area for this study. These areas are primarily used by HAFB for bombing and other munitions training and testing. Additionally, the DOD owns and administers the 321,000 ha (1240 mi<sup>2</sup>) Dugway Proving Ground. This area is used by the U. S. Army for testing and training of biological and chemical warfare systems. Combined, these DOD lands comprise some 15% of the total land area of the HAFB MOA.

By far the largest landowner in the MOA is the Bureau of Land Management (BLM). With nearly 3 million hectares (11,400 mi<sup>2</sup>) under their administration, the BLM controls over 63% of the land area of the HAFB MOA. Other significant landowners in the MOA include U. S. Forest Service, the Bureau of Indian Affairs, with two reservations within the MOA, and various Utah state agencies. Approximately 12% of the MOA is privately owned, including the municipal area around Wendover, Nevada and East Wendover, Utah.

The elevation in the HAFB MOA ranges from 1,265 m (4,150 ft) to 3,677 m (12,064 ft) above sea level. Over 80% of the MOA’s area is under 1,850 m (6,000ft). Geologically, the MOA is part of the Basin and Range Province (Hunt, 1974). The topography of this area is dominated by north-south trending “horst and graben”

mountain ranges and valleys, including the Grassy Mountains, the Deep Creek Mountains, the Newfoundland Mountains, the Pilot Range, the House Range, the Confusion Range, the White Valley, and Skull Valley. The area is also marked by the presence of two major evaporitic basins, the Great Salt Lake Desert and the Sevier Desert. These broad, mud- and salt-flat basin floors are representative of the interior drainage systems of the Great Basin, of which MOA is a part.

The MOA is within the temperate, semi-arid climate typical of the Great Basin, with a lake evaporation rate of over 40 inches per year (Tilton, 1998), but receiving only some 6 - 10 inches of precipitation per year (Sharik *et al.*, 2000; Tilton, 1998), principally in the form of rain or snowfall in the winter months. Evergreen Sub-Desert Shrub is the dominant vegetation cover type, with barren flats in the basin floors, grass steppes in the middle altitudes and evergreen woodlands in the higher altitudes.

#### *Central Nevada Basin and Range*

The Natural Resources Conservation Service (NRCS) has delineated the United States into geographically associated areas of similar soil type, climate, water resources and land use (Soil Survey Staff, 1981) called Major Land Resource Areas (MLRAs). These MLRAs are commonly used bounds in soil, vegetation, and natural resource planning, management, and research (Soil Survey Staff, 1981). One of these resource areas, MLRA 28b, was used to delineate the second study area for this work.

MLRA 28b, the Central Nevada Basin and Range resource area, located predominately in eastern-central Nevada and to a lesser extent in western-central Utah

(Figure 11), covers over 7.8 million hectares (30,170 mi<sup>2</sup>) of the central Great Basin. The major industry and land use within this area is livestock grazing and production of livestock feed (e.g. hay, grain) with some 1% or less of the total area given over to irrigated agriculture (Soil Survey Staff, 1981). More than 90% of the land in MLRA 28b is federally owned (Soil Survey Staff, 1981). With more than 6 million hectares (23,200 mi<sup>2</sup>), the BLM is the largest landholder in this study site, as it was in the MOA, administering some 77% of the lands in MLRA 28b. The U. S. Forest Service administers nearly 18% or nearly 1.4 million hectares (5,350 mi<sup>2</sup>) within MLRA 28b. Only about 340,000 hectares (1,300 mi<sup>2</sup>), or about 4%, of the MLRA is privately owned, and the remaining 1% of the land is owned or administered by various state and federal agencies.

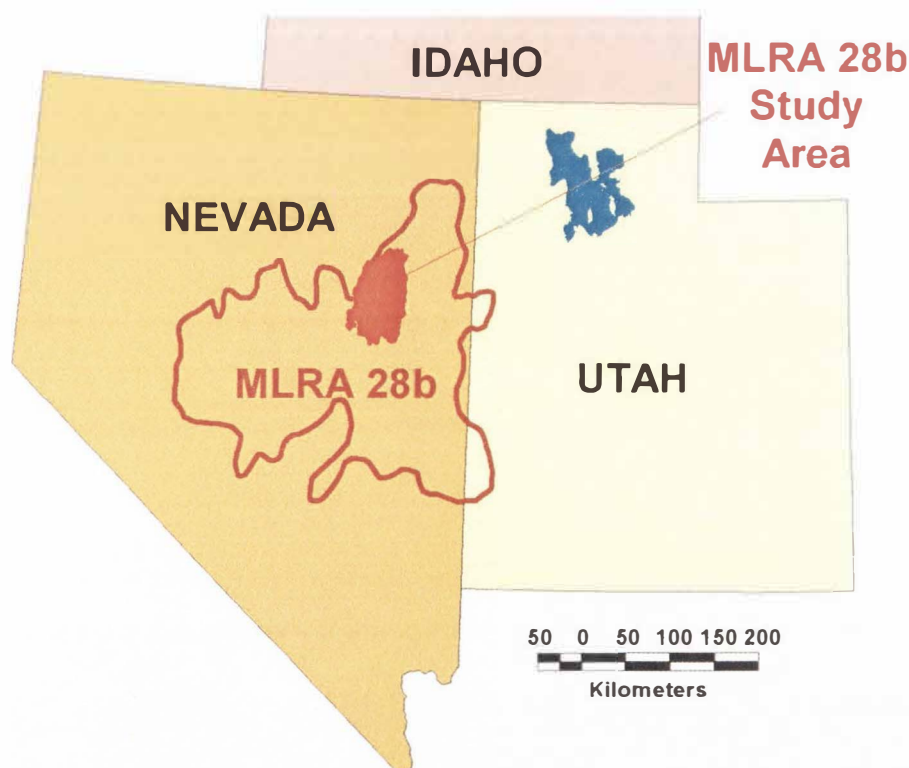


Figure 11. Location of MLRA 28b, Central Nevada Basin & Range.

Elevations in MLRA 28b range from about 1,450 m (4,760 ft) to over 3,600 m (11,800 ft). Typical of a Basin and Range landscape, the morphology of MLRA 28b is dominated by north-south trending “horst and graben” ranges and valleys, with steep, rocky mountains and flat, internally drained, basin floors. With only 5 – 25 inches of precipitation per year, this temperate, semi-arid landscape supports vegetation types common in the Great Basin, such as saltbush-greasewood in the lower elevations, and pinyon-juniper woodlands in the higher altitudes (Soil Survey Staff, 1981).

## METHODS

The course of the work in this study can be divided into two separate phases: model development and model assessment. The model development phase began in 1998, as a part of the HAFB TES Project. During this phase of the study, the theoretical and applied structure of the models were developed, as much by trial and error as by any other method, and Macroterrain Landtype classifications of the HAFB MOA, and the smaller UTTR North Range subset (Figure 10), were created. The work done in the model development phase was oriented towards the goal of creating part of a larger hierarchical land classification system. Piecewise assessment of any particular level of this hierarchy, as opposed to the performance of the classification system as a whole, was not a project priority.

The assessment phase of this study began in 2001, when it was determined that the methods and results of the Macroterrain level of the HAFB ECM classification warranted further study. This phase can be viewed as a retrospective assessment of the landtype models used in the 1998 study, to determine if their application was valid at the time, to assess which model performed better in a comparison with pre-existing geographical data, to assess their applicability to other parts of the Great Basin, and to determine if further work along these lines would be productive.

### *Data Set*

The initial phase of this study used 90 m (3-arc second) resolution Digital Terrain Elevation Data (DTED) that was available for the entire HAFB MOA. All DTEDs were

projected to the Universal Transverse Mercator (UTM) coordinate system, zone 12.

Additional work utilized 30 m (1-arc second) resolution United States Geological Survey (USGS) Digital Elevation Models (DEM) where available due to the superiority in the representation of the land surface when compared to DTEDs. The DEMs were used to analyze a small subset of the HAFB MOA and a small subset of MLRA 28b, at greater resolution than the original treatment. All DEMs were projected to UTM coordinates. Both raster data sets were analyzed in Arc/Info<sup>TM</sup> GRID.

Model assessment was performed utilizing three vector-format land characterization data sets. At 1:500,000 scale, Digital State Geological Maps of both Utah (Hintz, 1980; Ramsey, 1996) and Nevada (Stewart and Carlson, 1978; Turner and Bawiec, 1996) were used as the coarsest-scale assessment dataset. These vector data sets were used in conjunction with USGS geological attribute data (Raines *et al.*, 1996) to create 1:500,000 scale landtype association maps based upon surficial geologic material and landforms for the study areas (Figures 12 and 13). The Digital State Geological Maps are digitized versions of pre-existing paper or Mylar geological maps. They were chosen as an assessment dataset based on the extent of their spatial coverage (completely covering each respective state), and their extensive use and acceptance as a valid scientific dataset in the scientific community.

At 1:250,000 scale, the State Soil Geographic (STATSGO) Data Base from the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) was used as the moderate-scale assessment dataset. STATSGO coverage of Utah and Nevada were obtained along with their ancillary data tables, and were used to



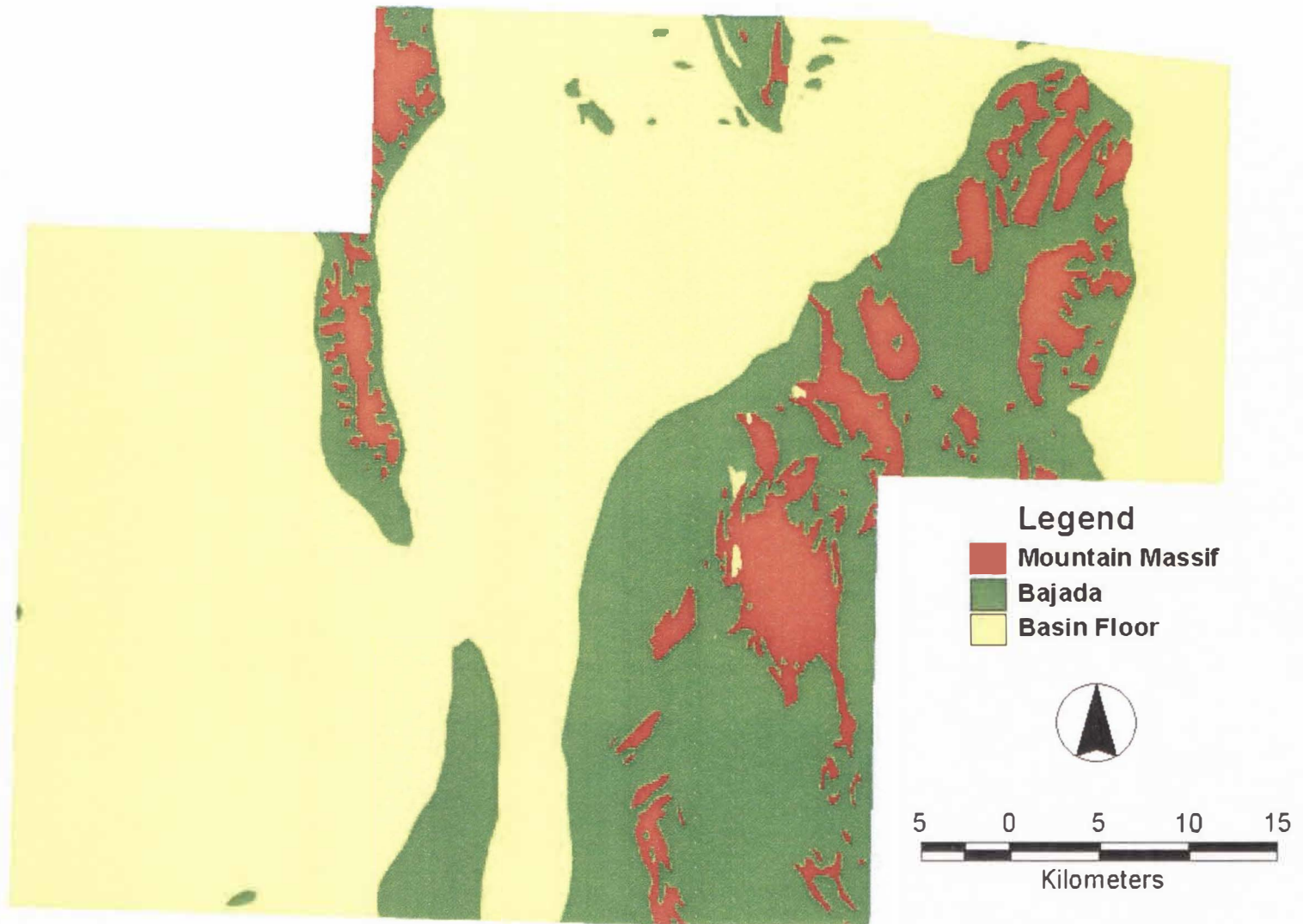


Figure 12. Geology-based Macroterrain Landtype Association Classification for the UTTR.



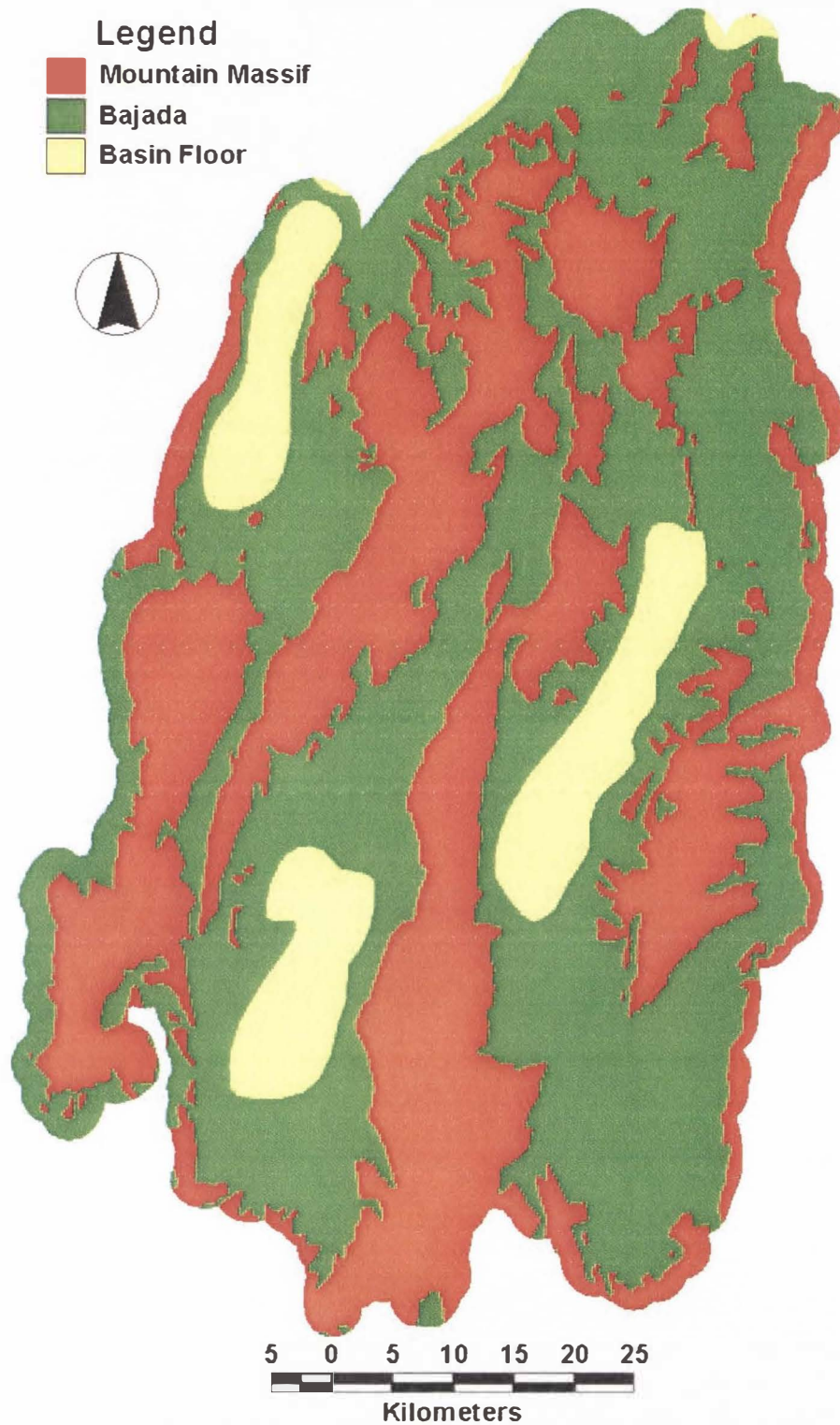


Figure 13. Geology-based Macroterrain Landtype Association Classification for MLRA 28b.

produce 1:250,000 scale landtype association maps of both study areas (Figures 14, 15). STATSGO is a commonly used dataset in natural resources research and management, and is popular for its easy accessibility, widespread coverage (100% of the U.S.) and associated attribute tables. The SSURGO coverage was used to create 1:24,000 scale landtype association maps of both study areas (Figures 16, 17). Mapped and compiled on a county-by-county basis at 1:24,000 scale, the Soil Survey Geographic (SSURGO) Data Base is the most detailed soil dataset available on a nation-wide scale. While SSURGO datasets are not as widely available as Geological data or STATSGO data, they are popular and effective data for natural resources research and management because of their fine spatial detail, and their associated attribute tables.

Because in the course of assessing the agreement of model outputs with the independent datasets, errors in registration would be assessed as errors in classification, efforts were undertaken to ensure the registration of the independent datasets to the DEM coverages of the study areas. While it was found that SSURGO was satisfactorily registered to the DEMs, minor adjustments had to be made to the STATSGO and Geological coverages. These registration corrections were performed heads-up at 1:24,000 monitor display resolution, and entailed aligning landforms delineated on the vector coverages with the corresponding landforms as seen in DEM shaded relief images, as well as co-registered Landsat Thematic Mapper (TM) imagery.

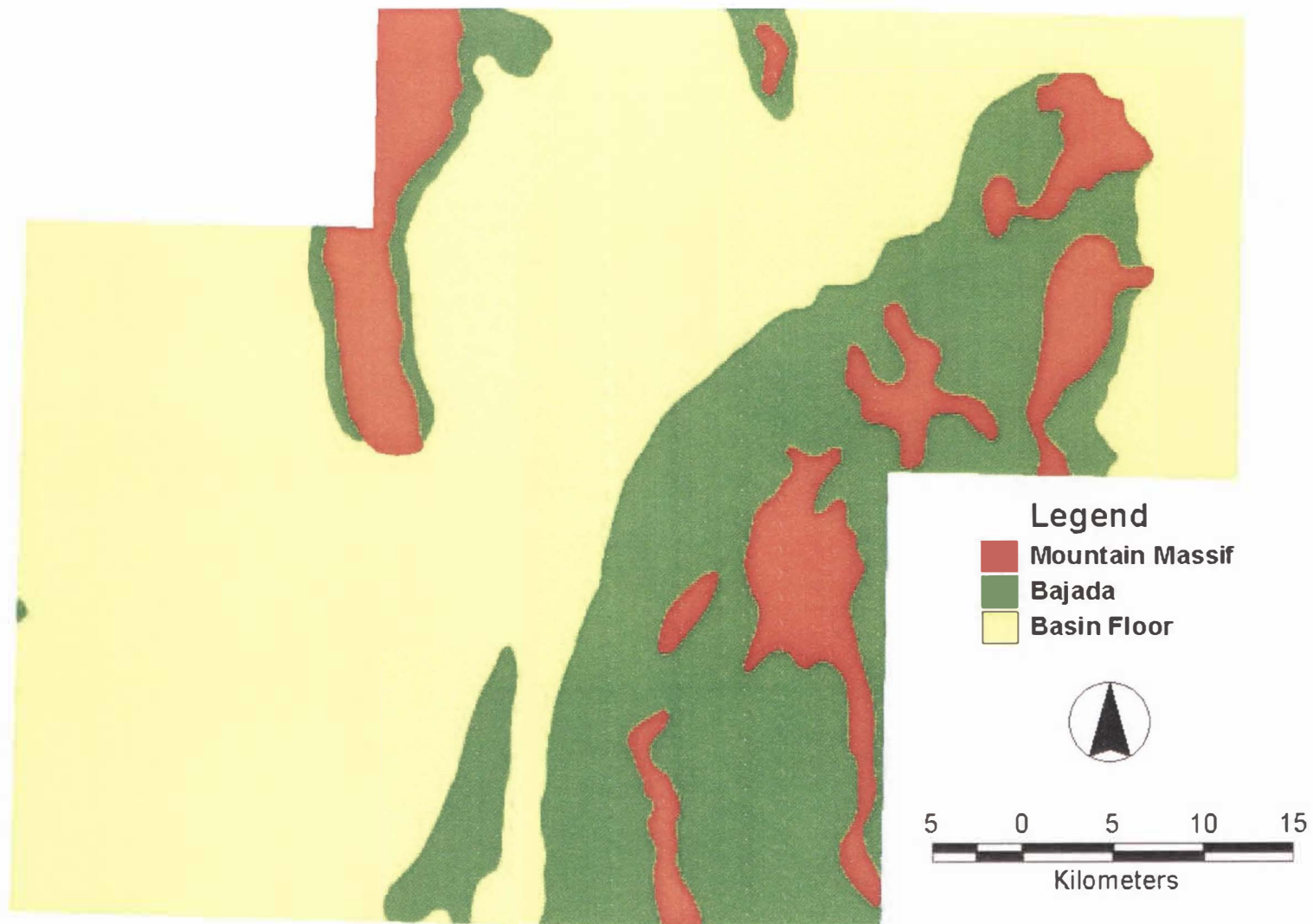


Figure 14. STATSGO-based Macroterrain Landtype Association Classification for the UTTR.

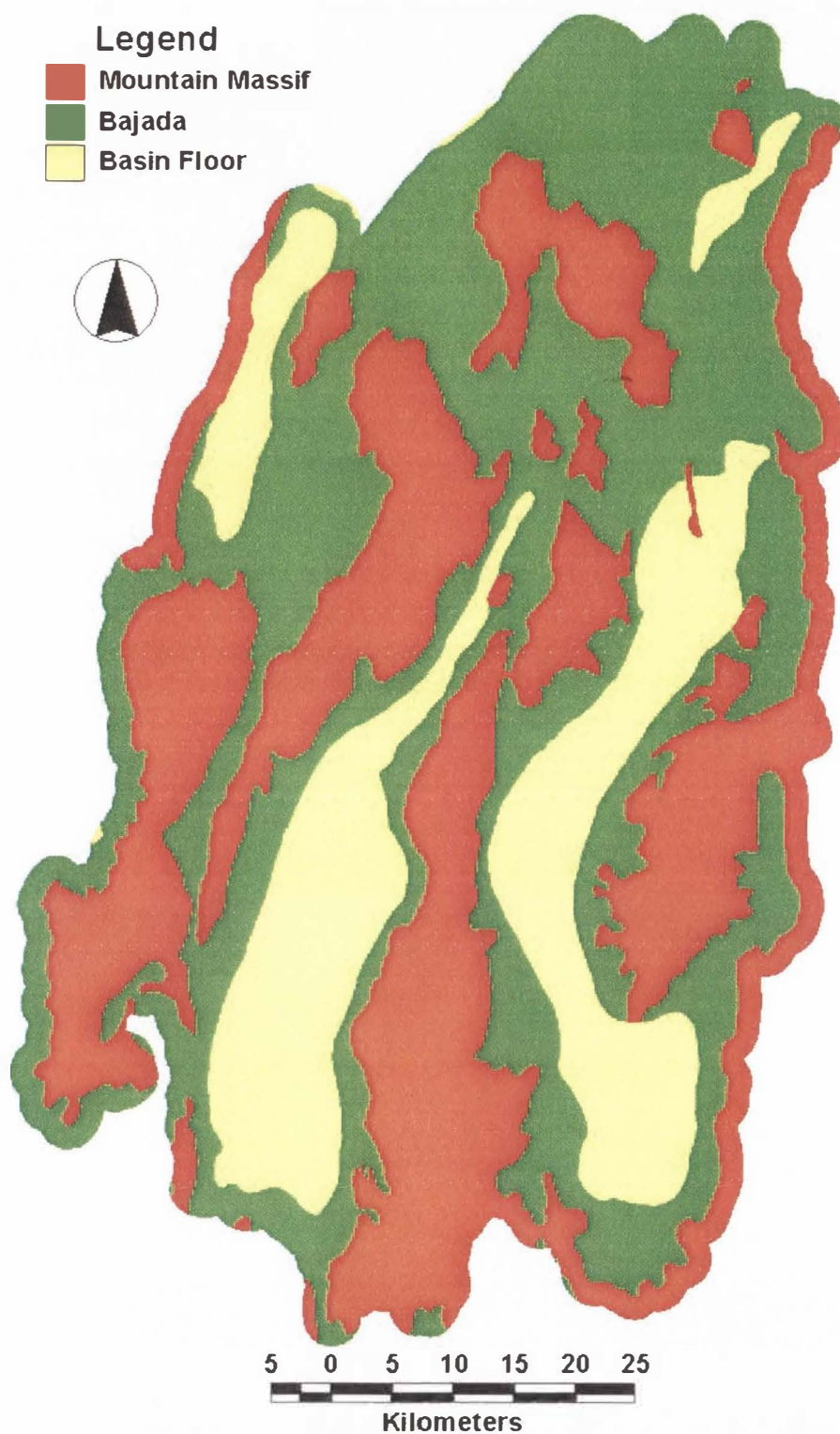


Figure 15. STATSGO-based Macroterrain Landtype Association Classification for MLRA 28b.



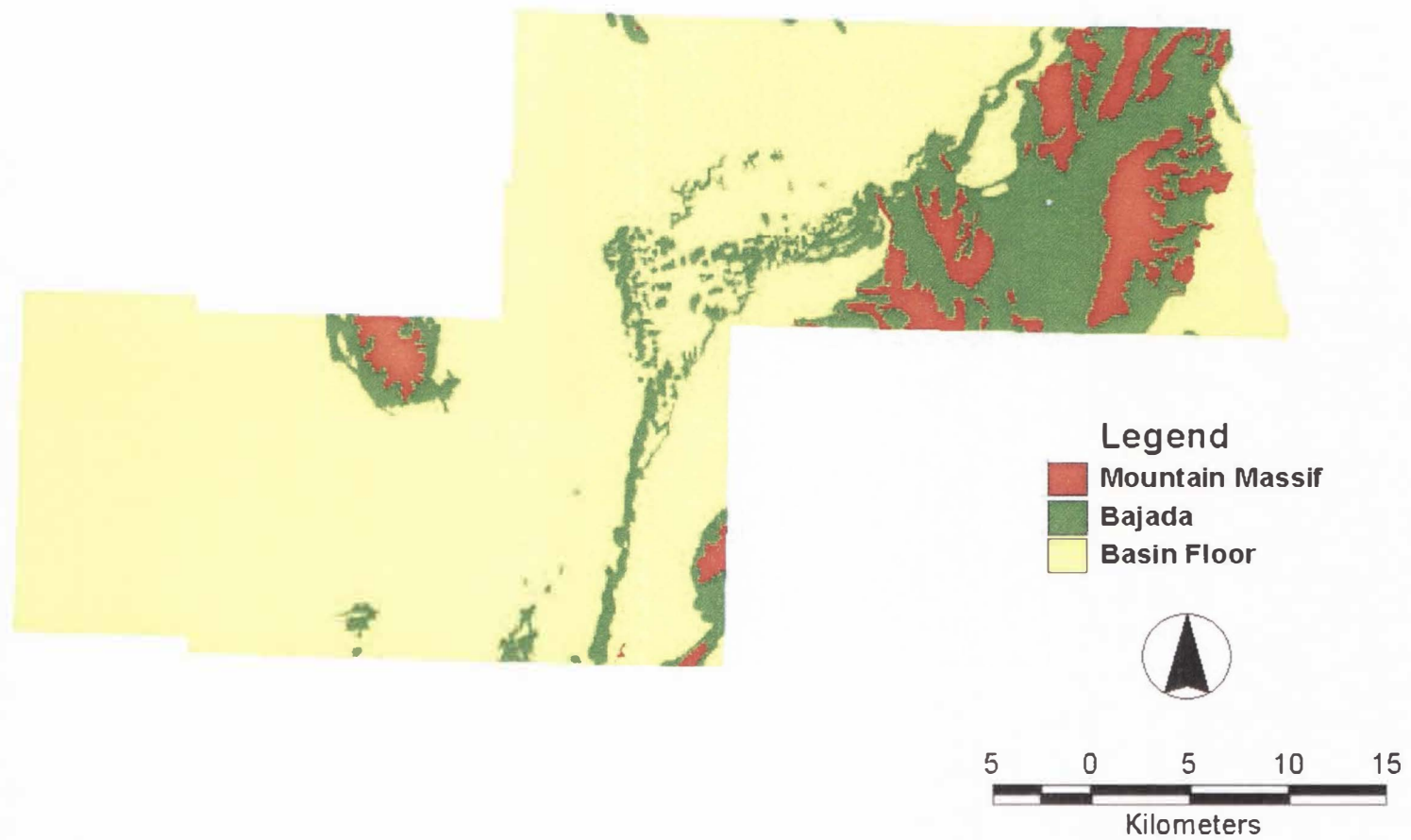


Figure 16. SSURGO-based Macroterrain Landtype Association Classification for the UTTR.

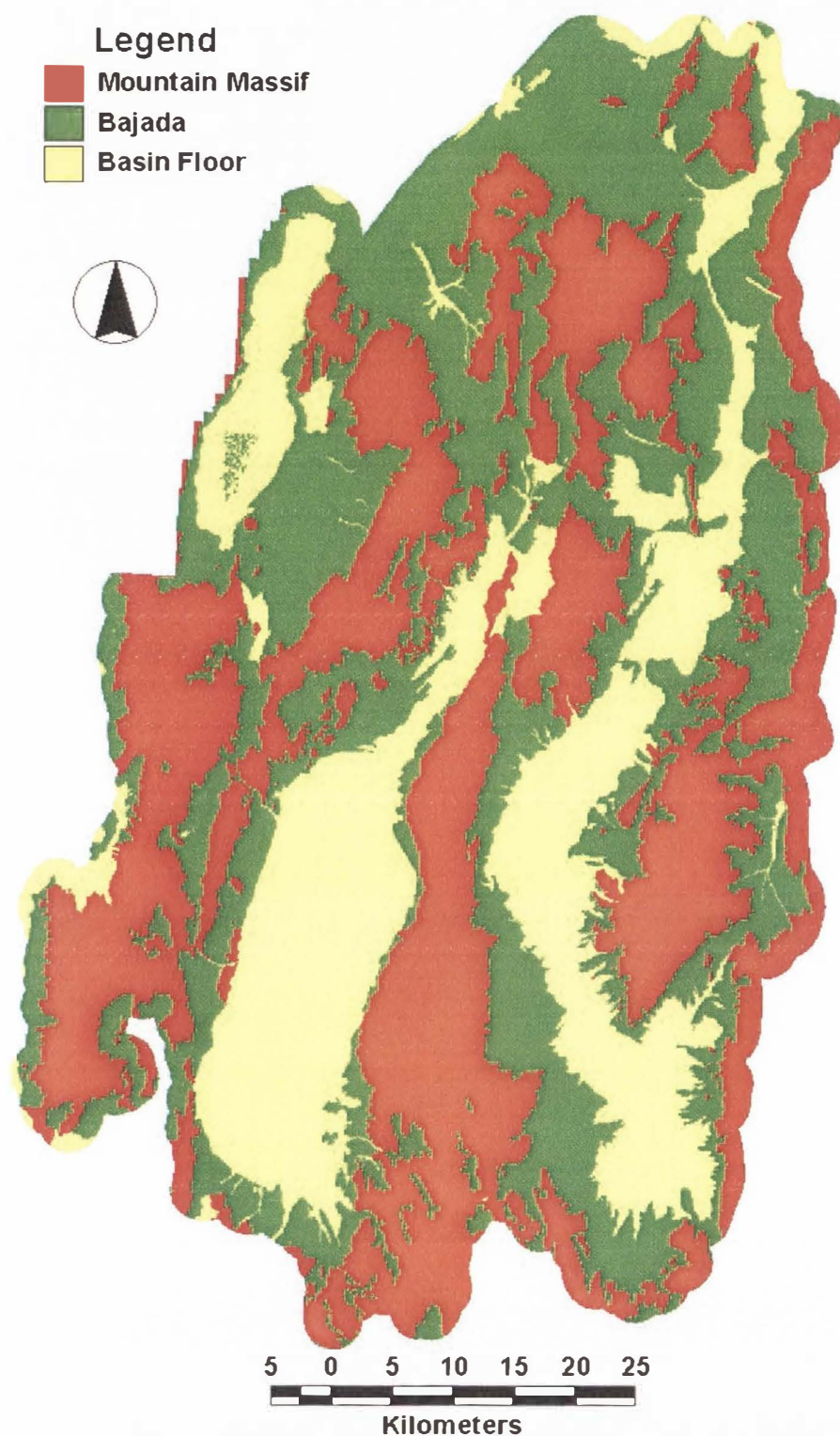


Figure 17. SSURGO-based Macroterrain Landtype Association Classification for MLRA 28b.

### *Model Development*

The first macroterrain model to be developed for the Hill TES Project was a slope-based deterministic model. Ideally, the slope of the landscape at any point would be indicative of that point's position in the landscape's energy continuum. Thus, slope thresholds could be used to delineate the three macroterrains as such:

Mountain Massif	slope > 15°
Bajada	15° > slope > 7°
Basin Floor	7° > slope

Analysis of the terrain for this model first involved producing a slope model of the study area from the elevation data. Application of the model consisted of applying a reclassification table to the slope model to produce three numerical classes which would be standard through further phases of this study: 3 (Mountain Massif, or Erosional Landtype), 2 (Bajada, or Transitional Landtype), and 1 (Basin Floor, or Depositional Landtype). Early in the implementation of this model, it was observed that though slope was ideally indicative of a location's position in the energy continuum, this was often not the case. For example, flat areas at high altitude such as alpine meadows would be classified as Valley Floor despite their high position in the energy slope. What was needed was an enforcement of superposition of the Macroterrain Landtype classes. That is, the model needed rules specifying:

- 1: Mountain Massif cells could not be downslope of Bajada or Valley Floor cells.
- 2: Bajada cells could not be downslope of Valley Floor cells.

This improvement on the slope-based classification utilized a flow-direction

model generated from the elevation model to enforce superposition. This model was developed as a GRID-based Arc/Info Macro Language program (AML) called *LTCLASS.AML* (Appendix A). All cells in the classification model were given an initial value of 1 (Valley Floor). All cells of a given threshold slope value or greater were then classified as 2 (Bajada), these cells were then submitted to the GRID watershed model as watershed pourpoints. Thus, all cells pouring into (hence up-gradient of) cells of class 2 were similarly classified as Bajada (Figure 18). These steps were then repeated with a second, higher threshold slope to classify cells as class 3, or Mountain Massif. This improved method produced the desired internally consistent Macroterrain Landtype units with no conflicts of superposition.

After the development of the slope-based deterministic model, it was felt that the classification of landforms could be further improved. The treatment of the data in order to utilize the GRID watershed model, i.e. filling in the sinks in the DEM to produce a continuously draining model, put the integrity of the input data and the robustness of the model itself in question. Furthermore, the model was ill suited to areas of non-characteristic slope, such as the I-80 levy running several meters above the floor of the Great Salt Lake Desert for the entire width of the MOA. It was determined that a supervised classification scheme may be able to distinguish between the three Macroterrain Landtype classes. Such a model would be automated enough to fit the needs of the ECM phase of the HAFB TES project, and may not require compromising the dataset.



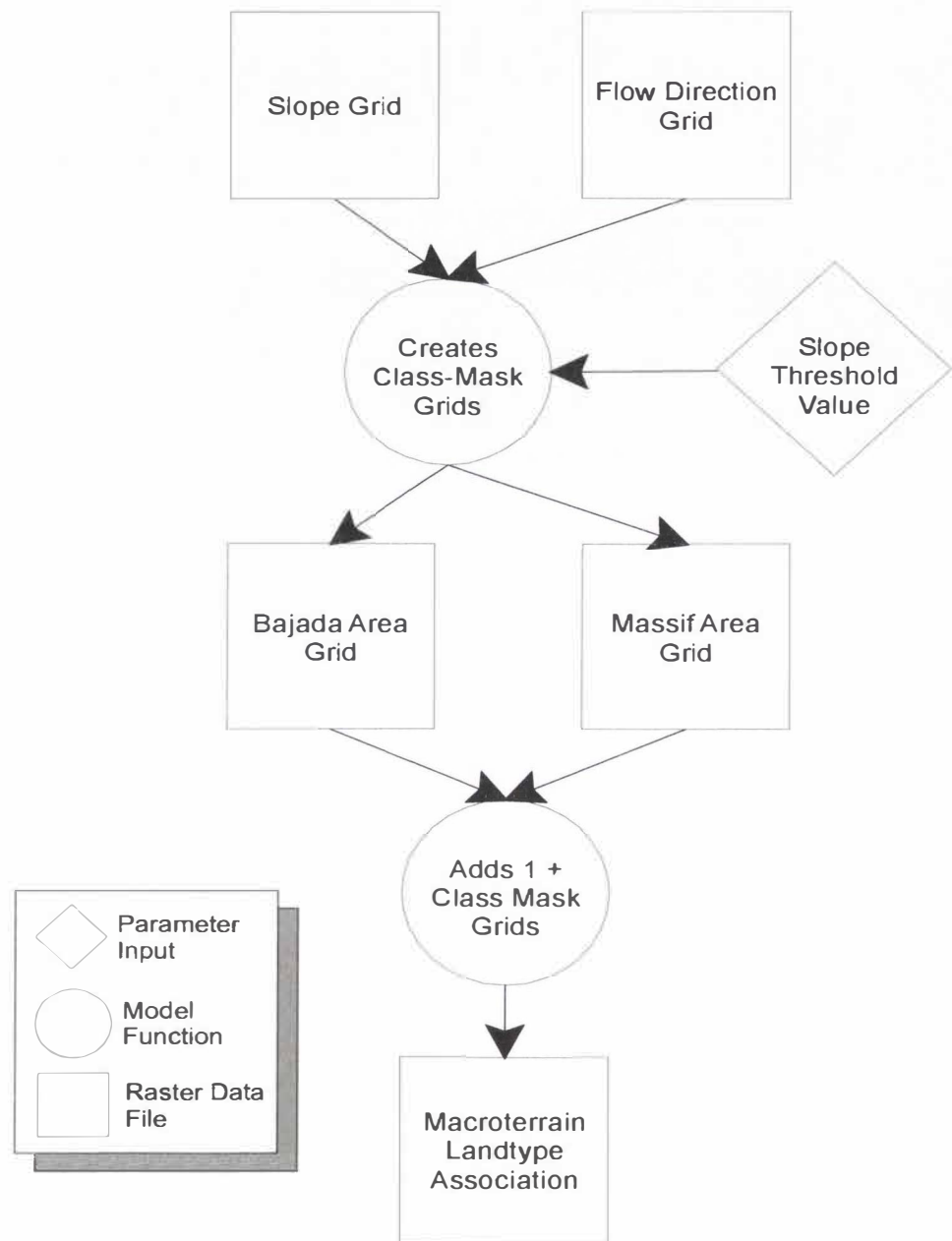


Figure 18. Logical Diagram of LTCLASS model.

The second model developed for the ECM section of the HAFB TES Project was a stochastic model, again using slope data. This was a supervised classification model, such as those often used in remote sensing applications. But instead of imagery input, as is usually the case in remote sensing modeling, this model was designed to classify terrain data. This model, referred to as *STATCLASS* (Figure 19), used class-type mask grids to delineate selected sample areas pre-determined by the user to be representative of each landform class, much like training data in a supervised classification. According to the  $N$ -value determined by the user, an  $N$ -number of random local values would be selected from the slope grid to be classified, strictly within the boundaries for each class-type mask. This task was called out by *STATCLASS.AML* (Appendix B) to be performed separately by an independent AML program called *RANDSAMP.AML* (Appendix C) (Tilton and Dougher, 1999), which limits the sample area, performs an  $N$ -number of samples, finds the mean and standard deviation of the sample population, and returns these values to the program which called it out. The mean and standard deviation of these samples would be determined thus, for each class separately.

The mean and standard deviation of each location (cell) in the grid to be classified was then calculated using a moving sample window, of a size determined by the user. The total number of cells in this moving window (e.g. 49 cells in a 7 X 7 window) serves as the  $N$ -value for the grid being classified. These values were stored in a mean value grid and a standard deviation value grid. Next, the  $t$ -value for each cell in the image was

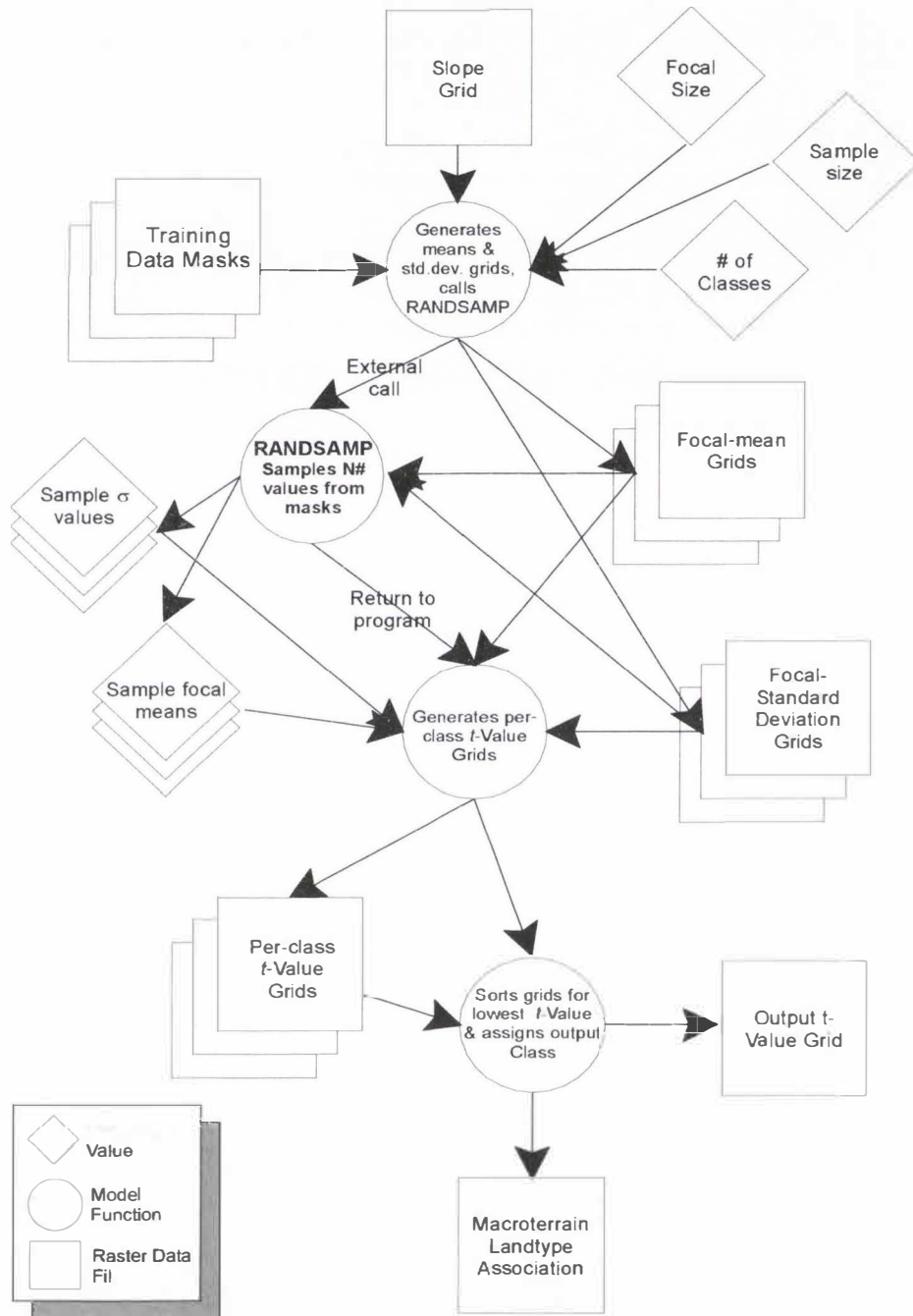


Figure 19. Logical Diagram of STATCLASS model.

calculated for each of the desired classes from the values from the mean and standard deviation grids and the scalar-value mean and standard deviation from the cell values sampled from each class-type mask (Equation 1). This provided quantification for each

$$t = \frac{|\bar{X}_{GRID} - \bar{X}_{Class}|}{\sqrt{\frac{\sigma_{GRID}^2}{N_{GRID} - 1} + \frac{\sigma_{Class}^2}{N_{Class} - 1}}} \quad (1)$$

location's similarity to each of the desired classes. Then, the  $t$ -values for each class were compared for every cell. The model assigns each cell the class with the lowest  $t$ , or least probability of a mismatch. The model also generates a grid of the selected  $t$ -values, so the user can analyze the strength-of-fit distribution across the classified area.

Upon completion and initial assessment of the  $t$ -value stochastic model, two issues of concern were called to attention. First, that though the output- $t$  grid provided an excellent view of the spatial relative strength of fit within the classified area, the determination of the output's absolute strength of fit, or confidence, was harder to determine. This is because the  $t$ -statistic in this case was being used not in a typical Boolean analysis (i.e. the population does or does not match the sample population) (Weinberg and Schumaker, 1965), but in a series of comparisons. In such an analysis, the confidence intervals interact in a manner that would be difficult to evaluate. The second issue of concern is the variation inherent in a classification scheme based upon random sampling. Though it was an intentional and hard-won aspect of the model, the random sampling did produce some variation in the output classification. To address these concerns about the stochastic model, a third model was needed. This model, a probability-output model referred to as PROBCCLASS was essentially an operational

variation upon the stochastic model, STATCLASS.

The PROBCCLASS model (Figure 20) was developed as an iterative version of STATCLASS. It uses the basic structure of STATCLASS, but performs this stochastic classification repeatedly for a number of iterations specified by the user (e.g. 100 iterations). The PROBCCLASS model uses four AML's (*RUNLOOP.AML*, *ITERCLASS.AML*, *RANDSAMP.AML*, and *PROBCCLASS.AML*) (Appendix D), as opposed to LTCLASS's one and STATCLASS's two, making it the most complex of the three models tested. *RUNLOOP.AML* controls the classification program *ITERCLASS.AML*, calling it to be run the number of specified iterations. *ITERCLASS.AML* is a version of *STATCLASS.AML* modified to be run by *RUNLOOP.AML* for the specified number of iterations, along with associated operational modifications to allow for non-interactive running. Each iteration of *ITERCLASS.AML* make calls to *RANDSAMP.AML* for the mean and standard deviation of a random sample (of constant number  $N$ ) of the training data, upon which that iteration's  $t$ -value derived classification is based. After the iterations are complete, *PROBCCLASS.AML* assesses the number of iterations in which each cell is assigned to a particular class and normalizes this to a real number percentage (i.e. 0-100). This percentage is that cell's probability of being assigned the given class with the given data and class-type mask. The probability grids for each class are then compared and an output classification is produced by assigning each cell to the class with the highest probability. This model greatly decreases the random sample-induced variation in the output classification, in comparison to that of its predecessor, STATCLASS. It also produces a strength of fit measurement, in the form

of the classification probability, which is informative in both a relative sense, across the classified area, and in an absolute sense, where one can see the probability (or the inverse uncertainty) of the classification as a whole.

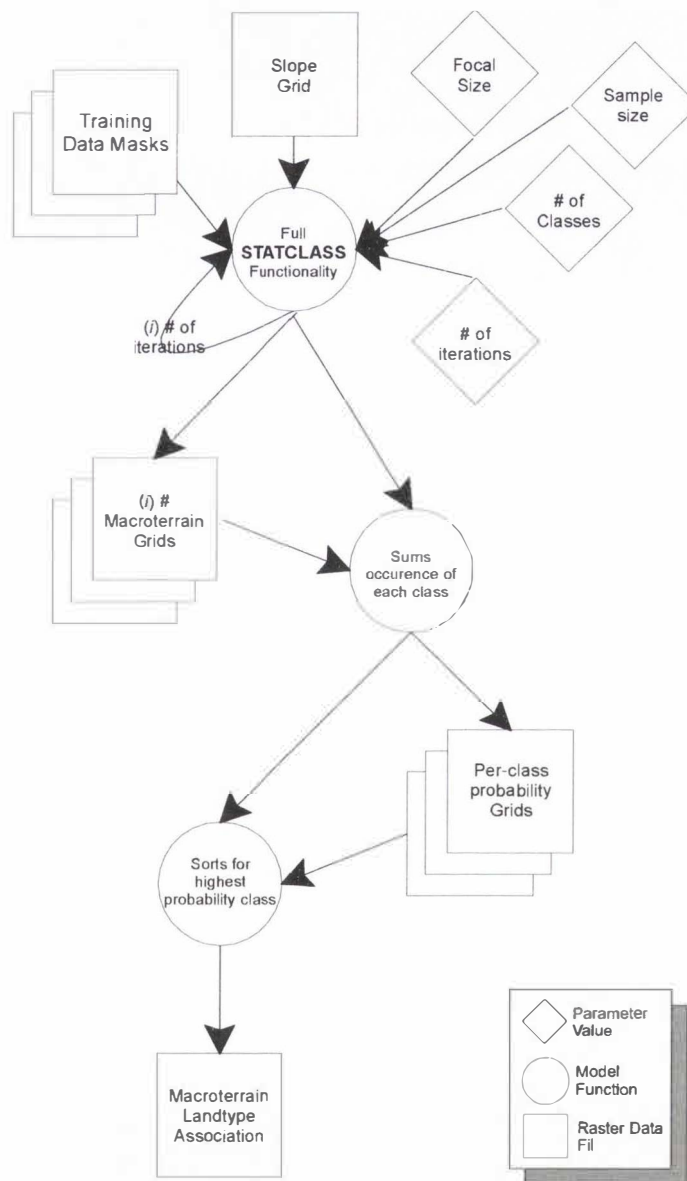


Figure 20. Logical Diagram of PROBCCLASS model.

### *Model Assessment*

In the development of the HAFB ECM classification system, there was no intent to ground truth each level of the classification in a piecewise fashion. Rather, the performance of the hierarchical classification would be checked as a whole by the bottom two levels of the classification, which were based on field data (West *et al.*, in press). As this study is an offshoot of that previous effort, it was determined that the assessment of the performance of the Macroterrain Landtype classification models should not require ground truthing *per se*, but that they should be assessed against other geographic data which might reasonably have been used at this level of the ECM system, had such modeling techniques been unavailable.

Since the original intent of the ECM system was to use the HAFB MOA as a proving ground to develop a classification system which could be applied throughout the Great Basin, and in limited areas beyond, as well as offering up a framework methodology which could be adapted by other managers and researchers to local study areas (West *et al.*, in press), it was decided that a second study site should be added to the assessment, in addition to the HAFB MOA site data. This would broaden the basis for the assessment, while still keeping the work within the bounds of the original intent of the ECM study.

The bounds for the HAFB MOA North Range study area were determined not by physical attributes, but by political/administrative borders. Coverage of the UTTR North Range, plus an additional mile-wide buffer along the southeastern margin of the North Range property line required for a concurrent study, required part or all of 22 1:24,000

USGS quadrangles. It was decided that the outer bounds of these conterminous quadrangles would form the boundary of the North Range study area (Figure 10).

It was decided that a subset of MLRA 28b, the Central Nevada Basin and Range, would serve as a second study site. This area was chosen for its central location within the Great Basin, for its climate, which is strongly representative of the Great Basin (Soil Survey Staff, 1981), and for its typical Basin and Range landform morphology and morphometry. The location of the subset was randomly chosen within the confines of MLRA 28b and was located in the north-central portion of the MLRA (Figure 11). The size of the MLRA 28b subset was chosen to be similar, but not equal to, the size of the HAFB MOA North Range. An area of approximately 50,000 km was delineated using natural bounds, rather than political boundaries, as is the case with the North Range. United States Geological Survey (USGS) Hydrologic Unit Code (HUC) boundaries were used as the natural bounds for the delineation of the MLRA 28b subset (Seaber *et al.*, 1987) as these bounds are commonly used in natural resource management and research for delineation of areas for management planning, and thus would approximate an area which might be used in a future independent application of these methods.

Having delineated both study areas by their respective means, all further methods shall be considered identical for the two areas, except where stated otherwise. With the study areas delineated, the required input data (see Data Set discussion) were acquired via various locations on the internet. Discontinuous data tiles (e.g. DEM quadrangles, SSURGO tiles) were merged together to cover each study area. Other data preparations were undertaken to assure agreement in units, projections, etc.



The three Macroterrain Landtype classification models discussed in this work utilize first order derivative data, based upon elevation. The first order derivative dataset, flow-direction is used in calculating contributing flow area for the first model, LTCLASS. Flow-direction was calculated from elevation (DEMs) by the Arc/Info command FLOWDIRECTION (ESRI, 2000). ESRI (2000) determines the direction of flow by applying Equation 2:

$$drop = \Delta z / d * 100 \quad (2)$$

where *drop* = the index of change in elevation from one cell to another,  $\Delta z$  = the change in elevation, and  $d$  = distance from one cell's centerpoint to another. Equation 2 is applied iteratively to a cell's eight adjacent neighbors (ESRI, 2000), and the direction in which the value of *drop* is greatest is determined to be the flow direction. If *drop* is the same in all eight adjacent cells, then the analysis neighborhood is expanded and more iterations of Equation 2 are applied (ESRI, 2000). The output direction is encoded as an integer from 1 – 255, with direction 1 equivalent to ordinal direction 90°.

The other first order derivative dataset, slope, is used in all three Macroterrain Landtype classification models. Slope is calculated in degrees (°) from elevation (DEMs) by the Arc/Info command SLOPE (ESRI, 2000), using Equation 3:

$$\theta = \arctan \left( \sqrt{\left( \frac{\Delta z}{\Delta x} \right)^2 + \left( \frac{\Delta z}{\Delta y} \right)^2} \right) * 57.29578 \quad (3)$$

where  $\Delta z$  = the change in elevation,  $\Delta x$  and  $\Delta y$  represent the change in horizontal position, and  $\theta$  = the degree slope. These equations are calculated for each cell's eight conterminous neighbors, and the highest value  $\theta$  is determined to be the slope for that

output cell (ESRI, 2000).

Being the simplest and quickest model to run, LTCLASS was the first Macroterrain Landtype model to be run on both study areas. As was the case in 1998, when the model was first developed, this was an iterative process. It was decided that the MLRA 28b study area would be classified first, then those classification criteria would be verified and fine-tuned using the data from the UTTR North Range, to produce a comprehensive set of criteria for delineating Great Basin Macroterrain Landtype Associations.

Several combinations of threshold slopes were tried, starting with the values derived from the developmental results from the original study: Massif  $\geq 15^\circ$ , Bajada  $\geq 7^\circ$ , Basin Floor  $< 7^\circ$ . Each LTCLASS output classification was overlain with TM imagery and a shaded relief grid generated by the Arc/Info command HILLSHADE (ESRI, 2000), to subjectively match the classification with the topography. Because the resolution of the data in this study were higher than the data used in the developmental work (30m DEMs vs. 90m DTEDs), the calculated slope values were quite different at the margins of landforms, and as a result, the development thresholds of  $15^\circ$  and  $7^\circ$  were not found to be accurate delineators of the landtypes for the current dataset. After several iterations, an ordinal series of Massif  $\geq 12^\circ$ , Bajada  $\geq 2^\circ$ , and Basin Floor  $< 2^\circ$  was found to match the topography well enough to proceed.

These same iterative steps were then run using the slope and flow-direction data for the UTTR North Range. The  $2^\circ$ -slope threshold for discriminating between Basin Floor and Bajada was found to be a good descriptor for the UTTR North Range, as it was

for the MLRA 28b. The 12°-slope threshold for discriminating between Mountain Massif and Bajada was found to be too high, classifying the lower areas of Mountain Massif as Bajada. After several iterations, a threshold of 10° slope was found to be an acceptable delineator of the UTTR North Range's Massif/Bajada margin. This value was then run through LTCLASS using the MLRA 28b dataset, and was found to not seriously deteriorate the subjective quality of the MLRA 28b delineation of the Massif/Bajada margin. Thus, a final ordinal series of:

Mountain Massif	slope > 10°
Bajada	10° > slope > 2°
Basin Floor	2° > slope

was found to be a subjectively acceptable set of criteria for delineating Macroterrain Landtypes in at least two areas of the Great Basin (Figures 21, 22). The further assessment of LTCLASS as a classification model will assume that these criteria represent the best-fit possible using this model.

Running the STATCLASS Macroterrain Landtype classification model requires much more time and preparation than running LTCLASS. Prior to running STATCLASS, training data must be delineated for each class. To this purpose, polygon shapefiles were created in ArcView (Figures 23, 24) using a combination of TM imagery and DEM-based shaded relief as a visual key. Each polygon in a shapefile delineates an area that is representative of that class of landtype. For each study area, shapefiles with at least two polygons were created to delineate representative areas of mountain massif, bajada,

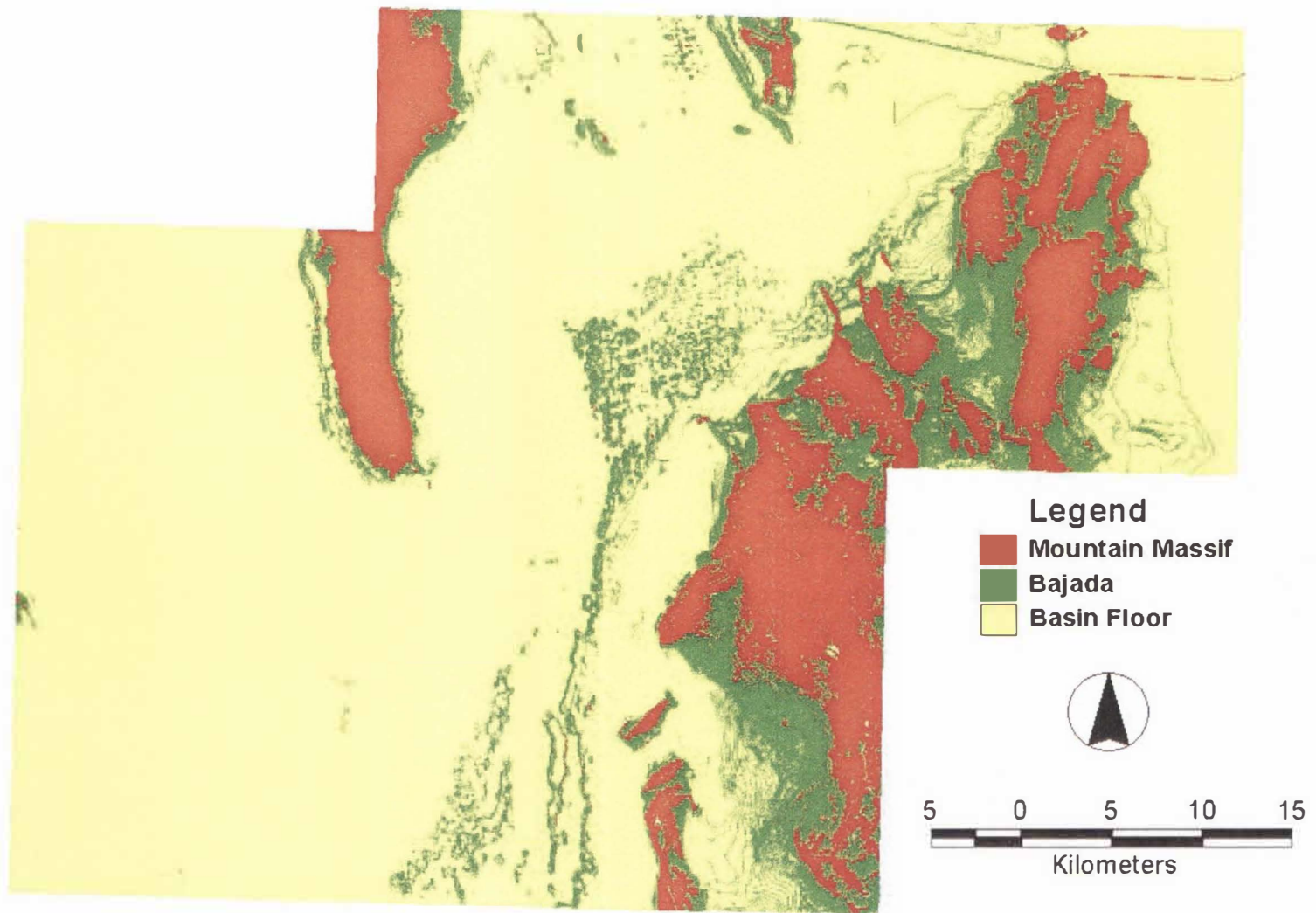


Figure 21. LTCLASS output Macroterrain Landtype Association map of the UTTR.



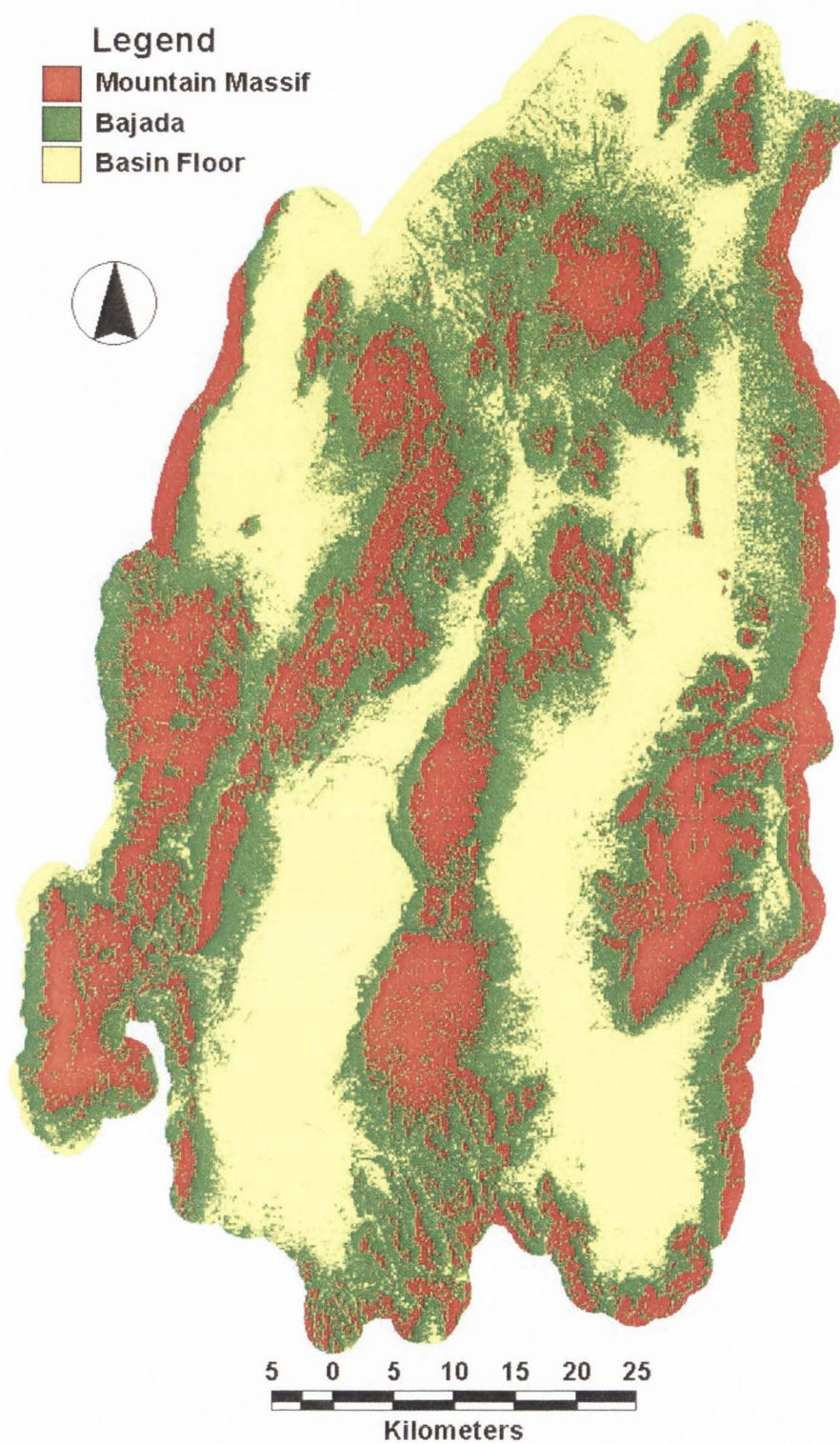


Figure 22. LTCLASS output Macroterrain Landtype Association map of MLRA 28b.

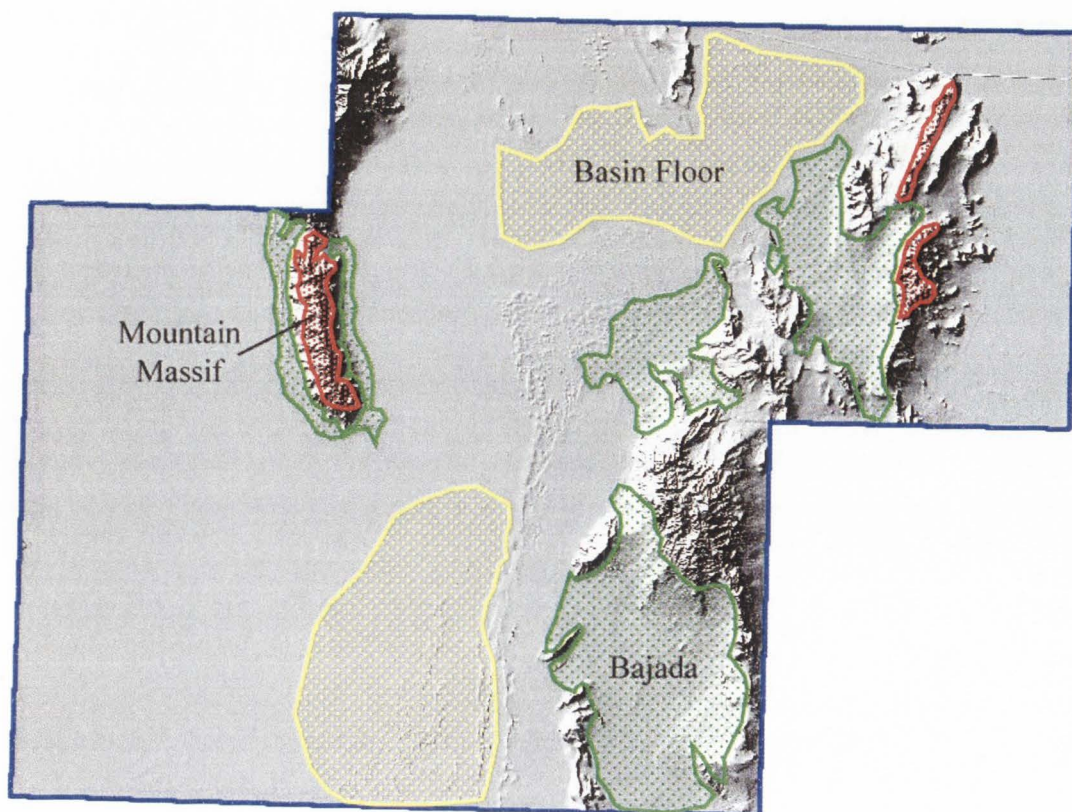


Figure 23. Example training data polygons for the UTTR.

and basin floor. The pixels delineated by these polygons, or *training data*, would be used by STATCLASS to establish the criteria by which each study area would be classified (Rees, 1999). These shapefiles are then converted into Arc/Info polygon coverages, and used to subset the study areas' slope grids with the GRID command POLYGONSELECT. The result of this step was six training data grids, one of each class (i.e. mountain massif, bajada, and basin floor) for each study area, within which the value of the training data would equal the study area slope grid, and the non-training data would have a value of NODATA.

Along with the slope grid of the study area, the training data grids are all the input data that are required to run STATCLASS. Upon running the program, the user is



prompted for these input data, along with the two user-specified criteria for the algorithm,  $N$ , the size of the moving focal-analysis window, and the number of classes. The number of classes was already determined to be three. The size of the focal window was set at 7 X 7, and the similar sample size  $N$ , was rounded up to 50. FOCALMEAN and FOCALSTD (focal-standard deviation) grids were first produced by STATCLASS using the 7 X 7

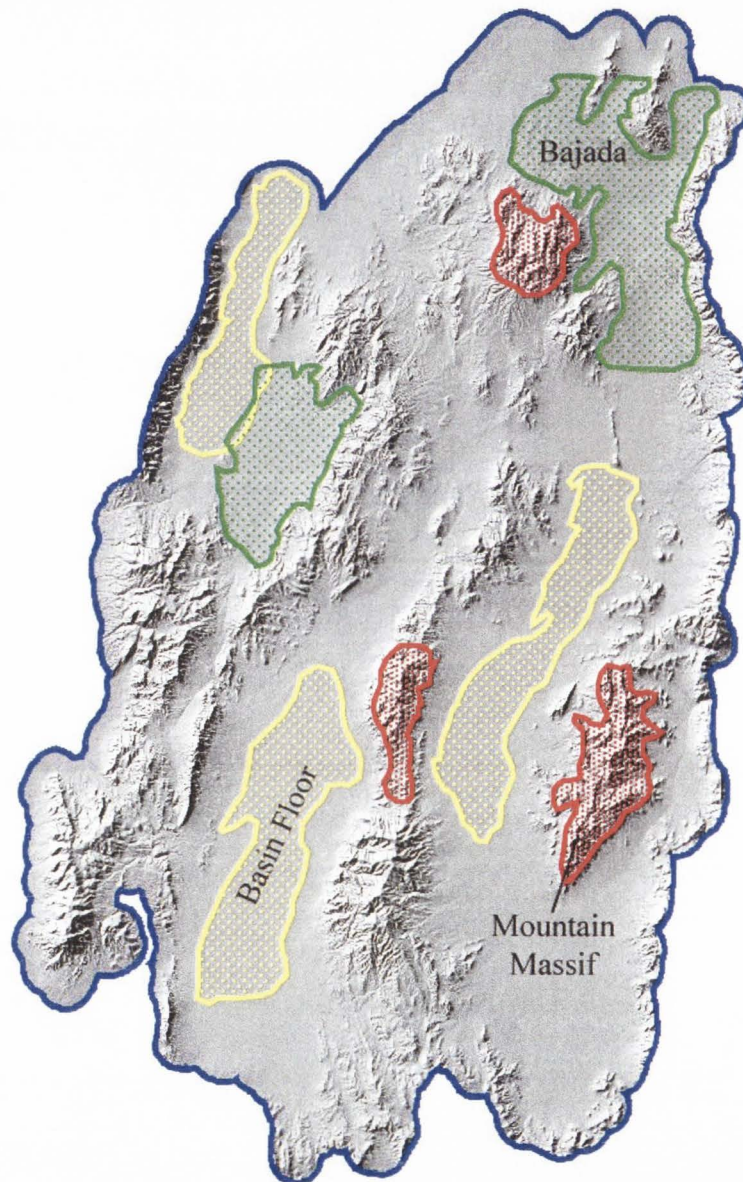


Figure 24. Example training data polygons for MLRA 28b.

window. Fifty point-samples were then extracted from each training data grid using RANDSAMP, and a mean value and standard deviation were computed from those sample populations. The use of an  $N$ -number sample population keeps the degrees of freedom manageably low in the following  $t$ -test, and allows the user greater freedom in the delineation of training areas by ensuring that all classes are represented equally in the  $t$  classification. Equation 1 was then used to compare the FOCALMEAN and FOCALSTD grid values to the mean and standard deviation of each sample population, resulting in a  $t$ -value output grid for each Macroterrain Landtype class (Figures 25, 26).

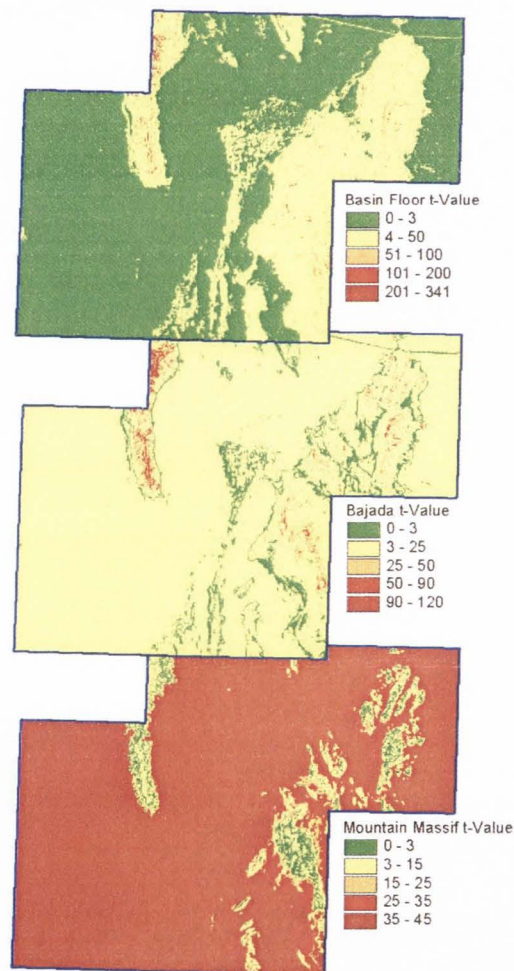


Figure 25. Example class  $t$ -Value grids for the UTTR.



STATCLASS then compared the three  $t$  grids for each study area, assigning each cell the class with the lowest  $t$ , and produced an output Macroterrain Landtype classification grid (Figures 27, 28) and an output final- $t$  grid (Figures 29, 30).

The same input data sets and criteria (i.e. focal window size,  $N$ , and number of classes) were used for PROBCCLASS as were used in STATCLASS, with the additional criteria of the number of iterations of the classification. The number of iterations was set

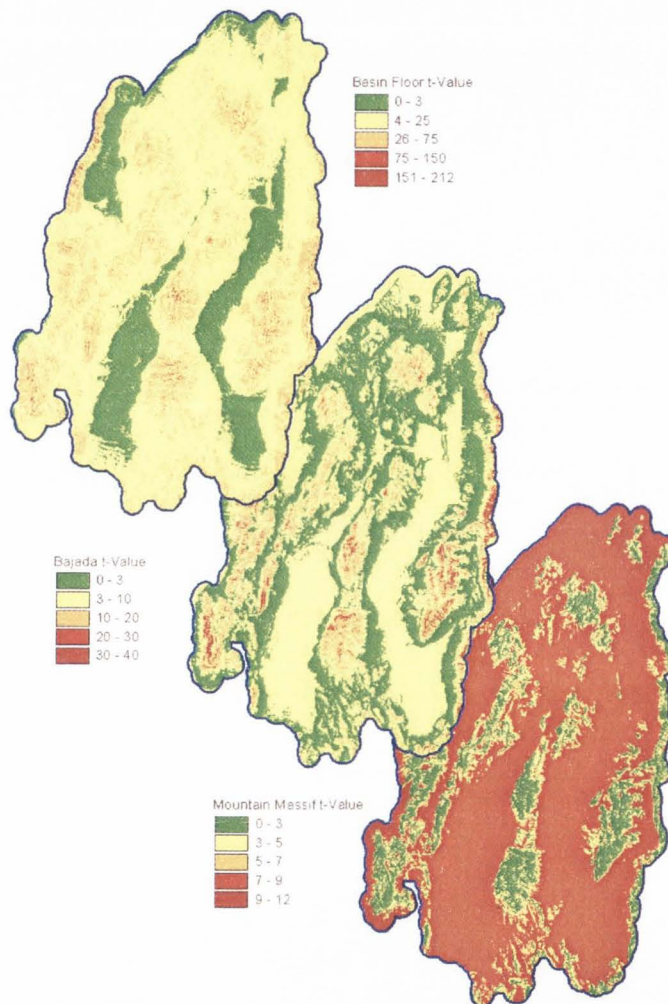


Figure 26. Example class  $t$ -Value grids for MLRA 28b.

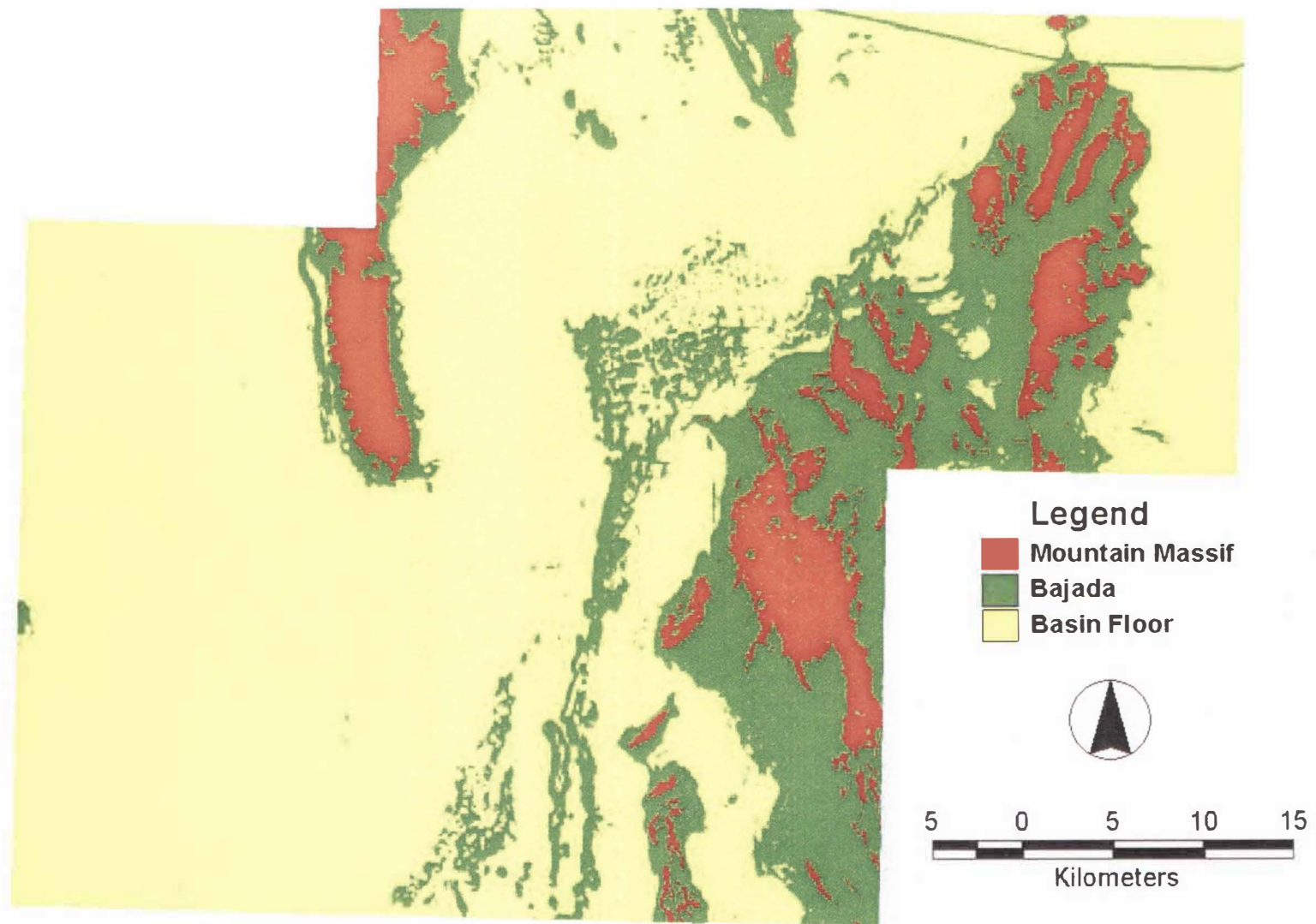


Figure 27. STATCLASS output Macroterrain Landtype Association map of the UTTR.

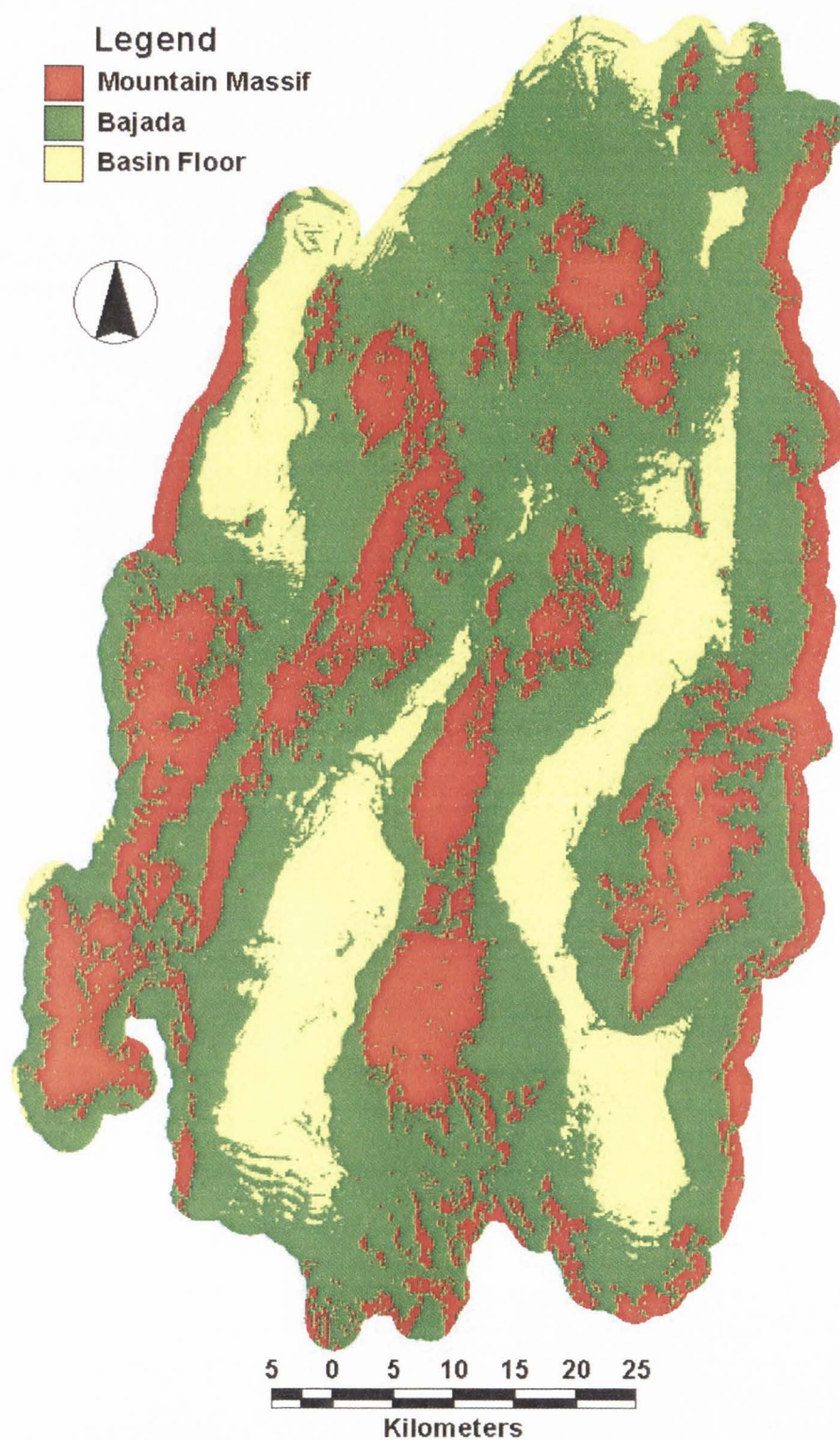


Figure 28. STATCLASS output Macroterrain Landtype Association map of MLRA 28b.



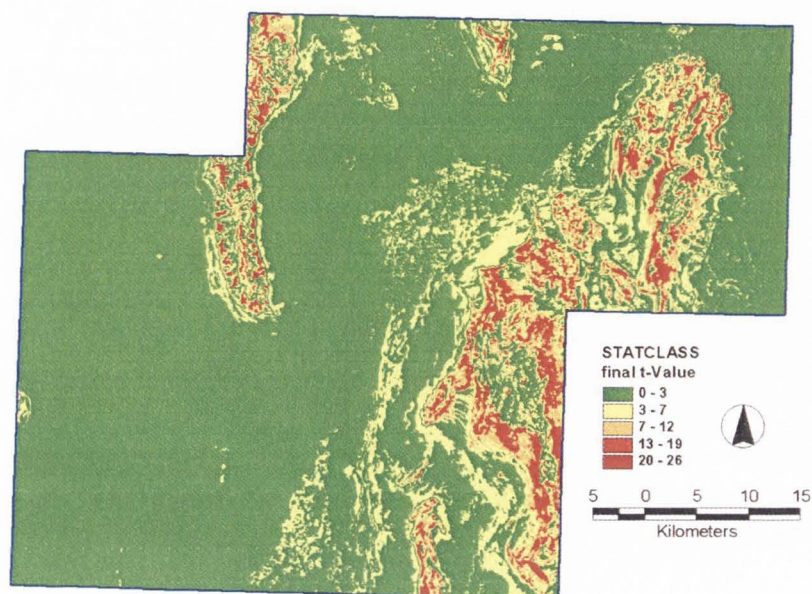


Figure 29. STATCLASS output  $t$ -Value map for the UTTR.

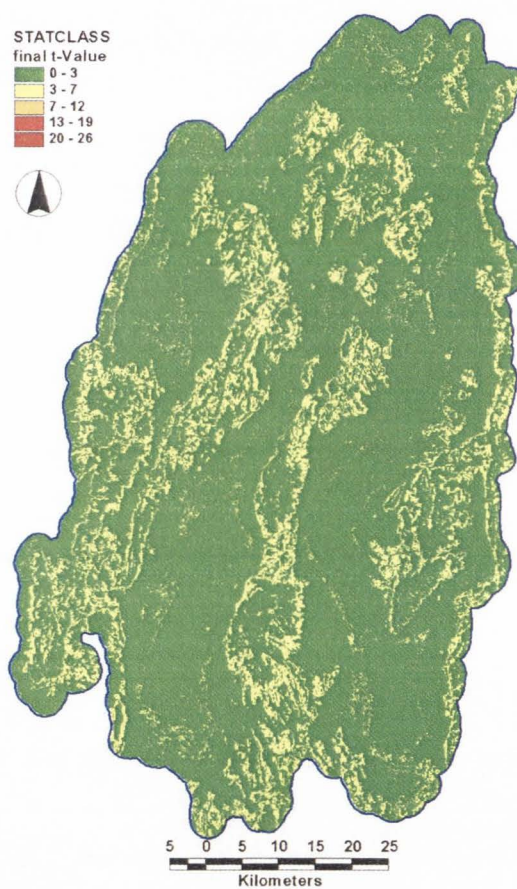


Figure 30. STATCLASS output  $t$ -Value map for MLRA 28b.

at 100, and all other input and criteria remained unchanged. PROBCCLASS then ran the STATCLASS algorithms 100 times, each time using a different randomly generated sample population, producing 100 Macroterrain Landtype classifications. The PROBCCLASS algorithm then counted the number of times each cell was assigned to each class (anywhere from 0 to 100) producing three class-probability grids for each study area (Figures 31, 32). The three class-probability grids were then compared and each cell was assigned the class with the highest probability (Figures 33, 34).

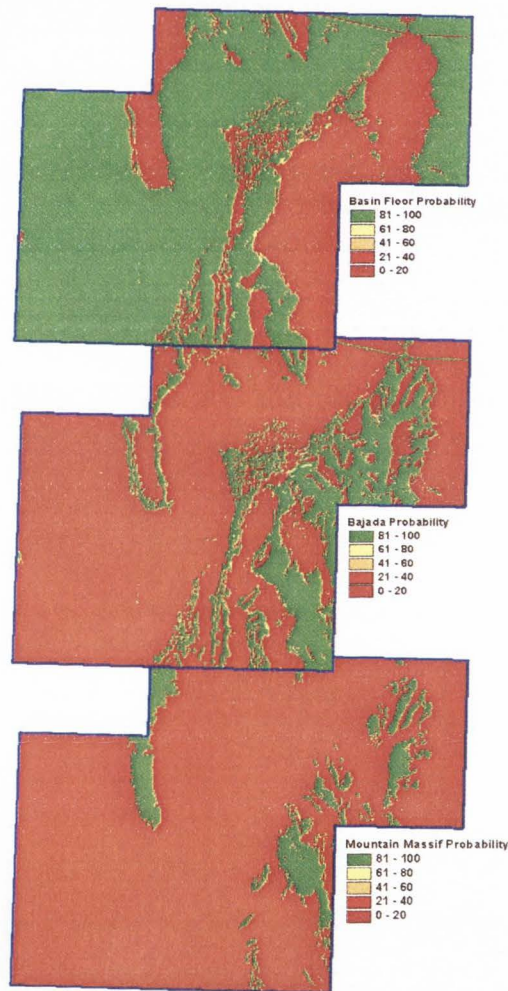


Figure 31. Class probability grids for the UTTR.

In order to compare the Macroterrain Landtype Classifications to independent data, the independent data must be similarly classified into three Macroterrain Landtypes (massif, bajada, and basin floor). To classify the Digital State Geological Maps, formation IDs were used in conjunction with interpretational attribute tables (Raines *et al.*, 1996) to identify the age and lithology of the geologic units. All surficial units of

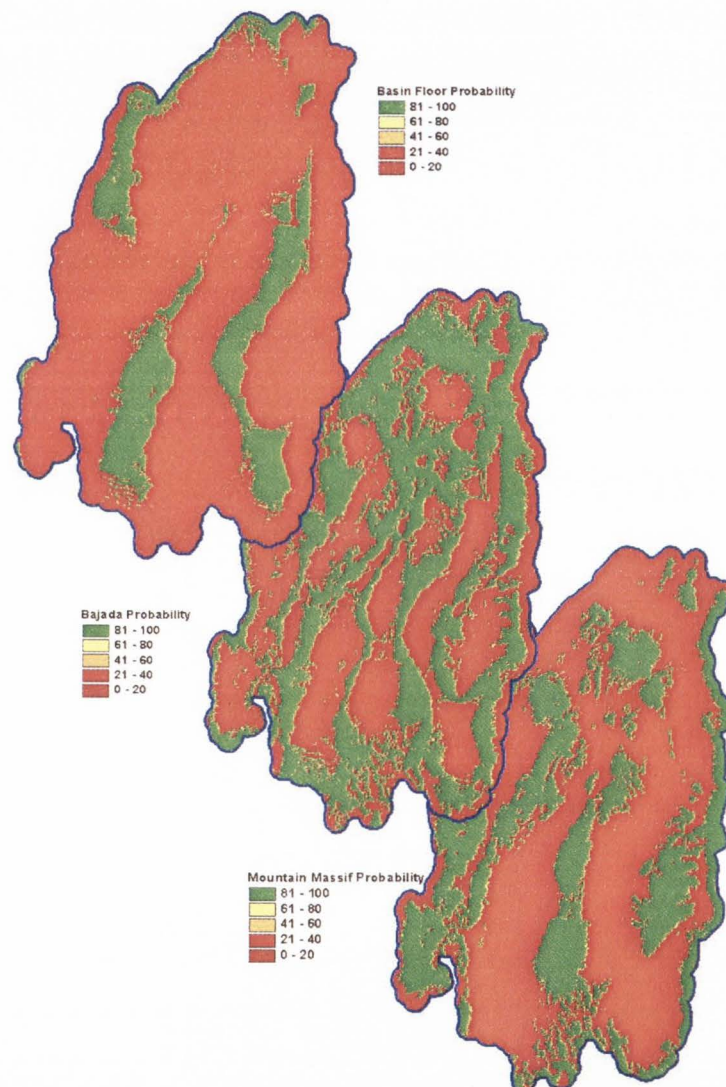


Figure 32. Class probability grids for MLRA 28b.



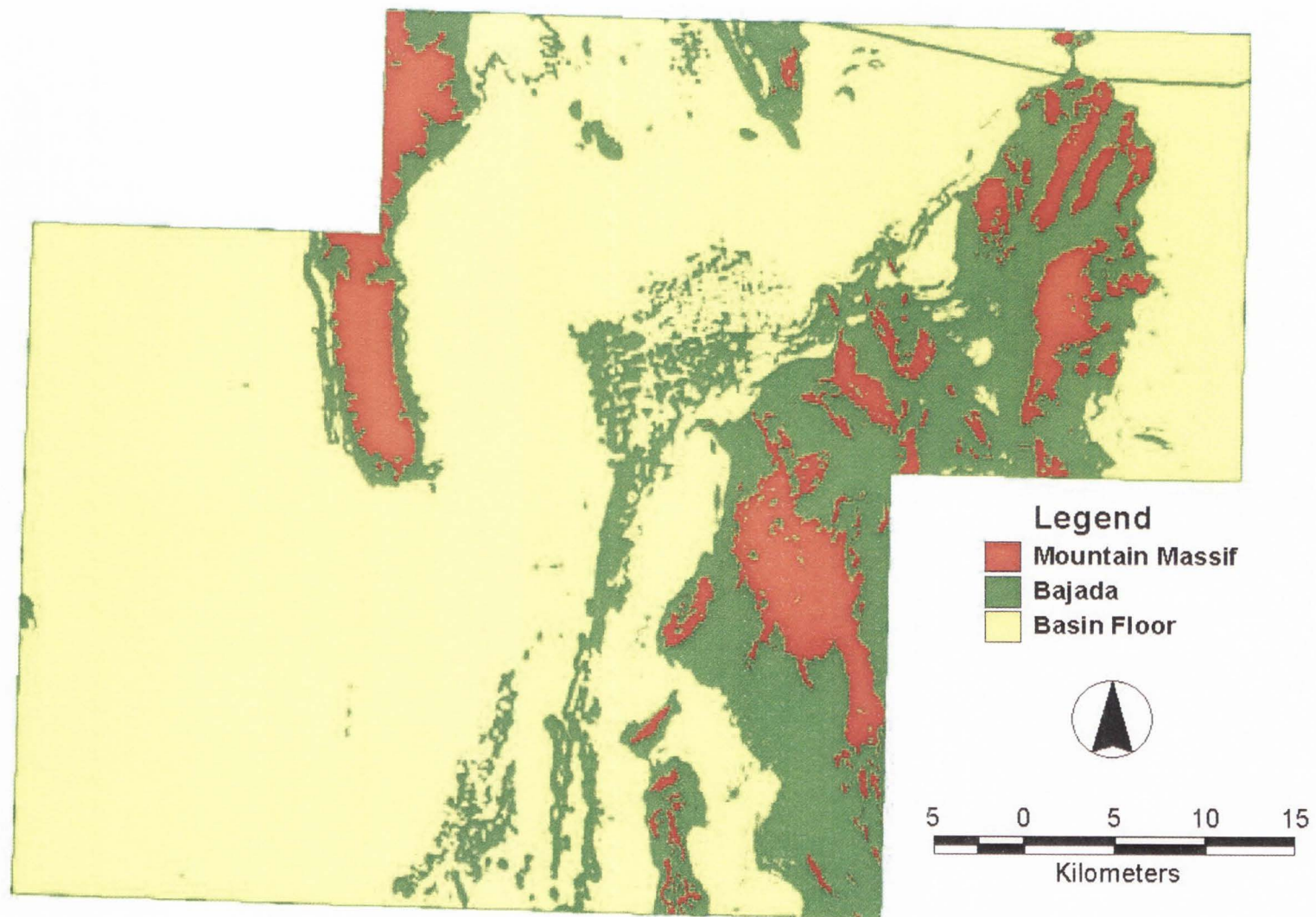


Figure 33. PROBCLASS output Macroterrain Landtype Association Map of the UTTR.

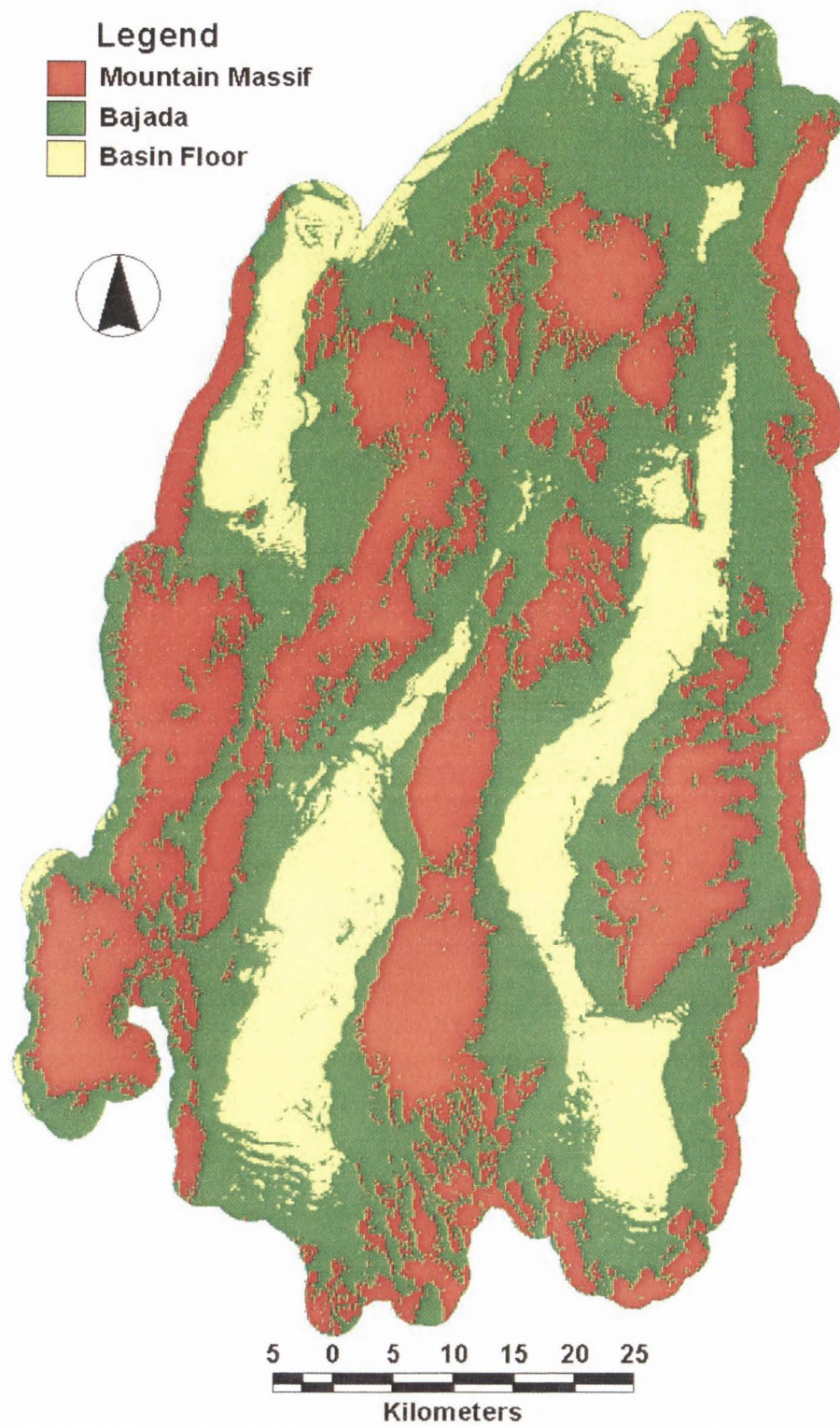


Figure 34. PROBCCLASS output Macroterrain Landtype Association map of MLRA 28b.



Tertiary origin or older were considered bedrock, and thus classified as erosional (Figure 35). Any unit of a purely depositional lithology (e.g. playa [Qp] or water) was classified as depositional (Figure 35). All other units (e.g. Quaternary alluvium [Qa]) were interpreted individually, largely being classified as transitional (Figure 35), with some units such as Quaternary basalt [Qb] falling in other classes. Units were given a numerical code related to their Macroterrain Landtype class (3 = massif, 2 = bajada, 1 = basin floor), and all boundaries between adjacent polygons of similar class were dissolved to create final landtype classified geology layers (Figures 12, 13). These vector layers were then converted to Arc/Info GRID format rasters, with projection and horizontal

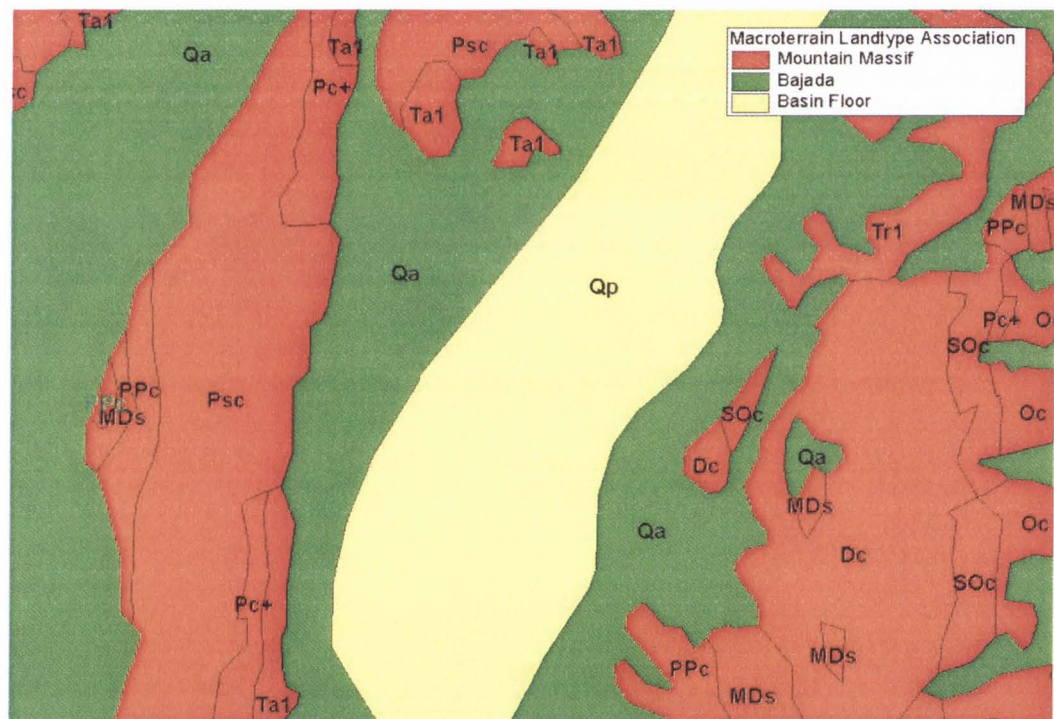


Figure 35. Detail of Macroterrain Landtype Association classified Geologic units from MLRA 28b.

resolution (30m) to match the model outputs, using the numerical landtype code as a grid value.

Because the STATSGO and SSURGO databases are related to each other, and because they have a similar attribute database structure, classification of these two datasets used similar criteria. The primary attribute for classification of these soil datasets was surficial texture. The tables *comp* and *layer* (Soil Survey Staff, 1991; Soil Survey Staff, 1995) were linked to the spatial attribute table by the common element *muid* (map unit ID) and used for delineating this criterion. Records with a unit sequence number (element *Seqnum*) 1 were selected so that the classification criteria would be applied only to the dominant or surficial layer of the soil unit (Soil Survey Staff, 1991; Soil Survey Staff, 1995). This step would be repeated several times as the classification of the *texture1* element was an eliminatory process, and the initial selection would have to be regained for each step of the classification. The first landtype to be classified was mountain massif, initially selecting for any unit with a texture of bedrock (weathered or unweathered) from element *texture1* in table *layer*. Further units were added to this selection by selecting units in which the reported minimum depth to bedrock was 14 inches or less, according to element *rockdepl* in table *comp*. A new field was added to the spatial attribute table for the STATSGO and SSURGO data coverages for landtype code, and all selected units were given the numerical code 3 to correspond with erosional landtypes.

The second step of the soil classification was to classify basin floor units. Bajada, or transitional units, were not classified for directly because the criteria for defining such

units are much broader and less defined than those for the other two units; bajada would be classified as everything not mountain massif or basin floor. With no transportation of sediment, the texture of the depositional basin floor units would be much finer than that of the other units. Units with reported fine textures such as silt, silt loam, clays, *etc.* were selected from element *texture1*, as were units reported to be water in element *compname* in table *comp*. The selected units were given a numerical landtype code of 1 to correspond with depositional landtypes. After this, all units not possessing a landtype code were classified as code 2, corresponding with transitional landtypes, resulting in complete landtype classified STATSGO (Figures 14, 15) and SSURGO (Figures 16, 17) layers. These vector layers were then converted to Arc/Info GRID format rasters, with projection and horizontal resolution (30m) to match the model outputs, using the numerical landtype code as a grid value.

With the completion of the landtype classification of the three independent data sources, the model outputs could now be evaluated. The preliminary analysis of model results in comparison to the independent data layers would begin with a basic assessment of map agreement. The Coefficient of Areal Correspondence (Equation 4) provides a

$$c_A = \frac{A \cap B}{A \cup B} \quad (4)$$

measure of the degree of relation between two areal distributions (Taylor, 1977), such as the distribution of Macroterrain Landtype units in a model output and an independent data layer. Equation 4 shows the coefficient as being a fraction of the area common to maps A and B ( $A \cap B$ ) where maps A and B classify the landscape similarly ( $A \cap B$ ) (Taylor,

1977). This analysis was performed in ArcView Spatial Analyst v2.0, using the Map Calculator. Binary identity grids were calculated where true (1) value cells represent cells with similar values in both grids of a pair, and false (0) value cells represent cells with dissimilar values. Cells which exist in one grid of a pair but not in the other were classified as NODATA and eliminated from the analysis. One such analysis was run for each possible combination of model output and independent data. Further, model outputs were similarly compared to assess how well the various modeling methods agreed with each other. The three independent data layers were also compared to each other, to assess their agreement. In the end, 30 binary identity grids were generated, 15 for each study area (Figures 37-41), covering every possible combination of the six grid types in the dataset (LTCLASS, STATCLASS, PROBCCLASS, Geology, STATSGO, and SSURGO). The number of cells of each value (true or false) were then compiled, and Equation 4 could be solved by the number of true cells ( $A \cap B$ ) divided by the total number of cells ( $A \cup B$ ) (i.e. number true + number false).

The second phase of the assessment of the agreement between the model outputs and the independent data was an analysis of the errors in the model classifications (relative to the independent data) by the construction of *error matrices*. An error matrix is an  $n$  by  $n$  array, where  $n$  is the number of classes, wherein the rows of the array represent the classes in the reference image, and the columns of the array represent the image being assessed (Campbell, 1987). The value of each cell in the array equals the number of cells in the study area which have been classified with the values specified by that row and column. The sum of values in a column represents the total number of cells given that



class in the image being assessed, and the row totals represent the values of the reference image classes (Campbell, 1987). The error matrix allows for more than the simple assessment of areal agreement, like that of the coefficient of areal correspondence (Equation 4). It allows for the categorical assessment of classification agreement, on a class by class basis. It also allows for the user to distinguish between errors of commission (type I error) and errors of omission (type II error), again on a class by class basis. The error of commission represents the fraction of the area of a given class of the model output which has been mis-classed as compared to the reference image (Campbell, 1987; Weinberg and Schumaker, 1965). The error of omission represents the fraction of the area of a given class of the reference image that was mis-classed in the model output (Campbell, 1987; Weinberg and Schumaker, 1965). The analysis of such errors illustrate the performance of the models on a class by class basis, and the assessment of both types of error is necessary to understand the nature of the classification error. For example, one model's classification of bajada could have a very low type II error (error of omission) by correctly classifying all areas in the reference image's bajada area (Campbell, 1987). This might appear to be a good match for this class, with a high percentage of agreement. But if the bajada class also has a high type I error (error of commission), indicating that many cells in the reference image's massif and basin floor areas have been classified as bajada in the model's output, we can determine that the criteria for defining the bajada in the model were too broad, or that the criteria for massif and basin floor were too narrow (Campbell, 1987).

The final phase of the model assessment was an analysis of model performance by

the calculation of *kappa* ( $k$ ) statistics for each model versus each independent dataset. Kappa quantifies the real agreement between model output and reference dataset over the amount of agreement one might expect by random chance. The higher the  $k$  value, the better the model has performed versus chance agreement. Equation 5 (Campbell, 1987) defines the *estimated*  $k$  (“ $\hat{k}$ ”) where “Observed” designates the accuracy reported

$$\hat{k} = \frac{\text{Observed} - \text{expected}}{1 - \text{expected}} \quad (5)$$

in the error matrix, or the Coefficient of Areal Correspondence, and “expected” represents the agreement which can be attributed to chance (Campbell, 1987). Calculation of “Observed” had already been performed by this point of the assessment, in the error matrix. Calculation of the expected chance agreement required the construction of another set of matrices. The cells of these matrices would contain the values of the products of the row and column marginals (totals) from the error matrices, resulting in a nine-cell matrix for a three-class system such as the Macroterrain Landtype Classification. The expected agreement by chance is the sum of the products of corresponding marginals (diagonal entries) divided by the sum of all marginal products (Equation 6) (Campbell, 1987). Nine  $\hat{k}$  values were calculated for each study area,

$$\text{expected} = \frac{\text{sum of diagonal entries}}{\text{grand total}} \quad (6)$$

corresponding to all combinations between model outputs and reference datasets. These values were then assembled into a matrix for assessment of the various models’ performance.

Given these three forms of numerical analysis, the performance of each model against the three independent datasets was assessed to estimate which reference dataset was most closely emulated by the given model. The performance of the model classifications were likewise compared each other to determine which, if any, model performed best given all three reference datasets.



## RESULTS

### *Preliminary Analysis*

As discussed earlier, the preliminary analysis of model performance was done by calculation of the Coefficients of Correlation for each of the models and reference datasets versus each of the other datasets. This analysis was performed for each study area separately by applying Equation 5 to the identity grids (Figures 36-41). Table III shows the correlation coefficients for the UTTR, wherein we see that the strongest correlations between model outputs and an independent dataset are the .916 correlation between STATCLASS and SSURGO, and the .913 correlation between PROBCCLASS and SSURGO. The equivalent performance of STATCLASS and PROBCCLASS in the case of classifying the UTTR is emphasized by the .979 correlation between those two model outputs, versus their correlation with LTCLASS of .887 and .881 respectively. In the case of the UTTR, the SSURGO reference dataset had the highest correlation with each of the three models. Of all three models, LTCLASS had the lowest correlation coefficient with each of the three independent classifications, having a maximum correlation of .897 with the SSURGO-based Macroterrain Landtype Association classification.

Table III. Correlation Coefficients for the Utah Test and Training Range (UTTR).

	LTCLASS	STATCLASS	PROBCCLASS	Geology	STATSGO	SSURGO
LTCLASS		0.8871	0.8811	0.7781	0.7752	0.8968
STATCLASS	0.8871		0.9798	0.8032	0.7917	0.9155
PROBCCLASS	0.8811	0.9798		0.8057	0.7953	0.9126
Geology	0.7781	0.8032	0.8057		0.8649	0.8365
STATSGO	0.7752	0.7917	0.7953	0.8649		0.8165
SSURGO	0.8968	0.9155	0.9126	0.8365	0.8165	

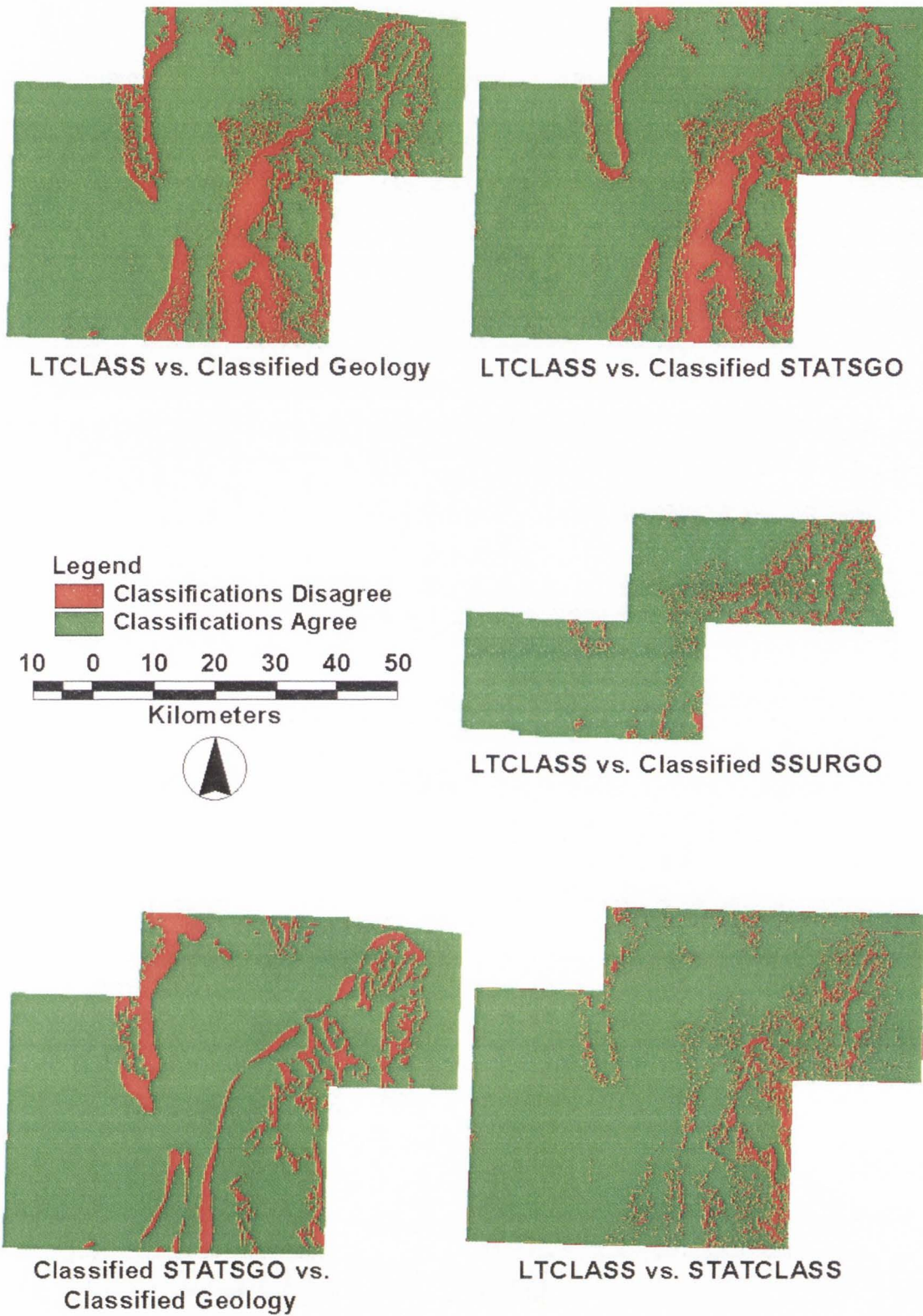


Figure 36. Classification comparison identity grids for the UTTR.



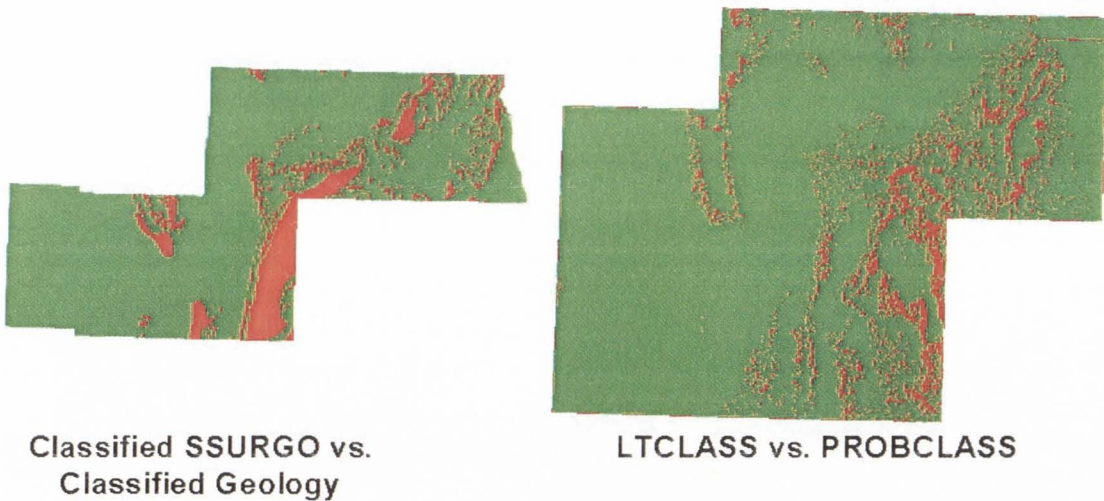
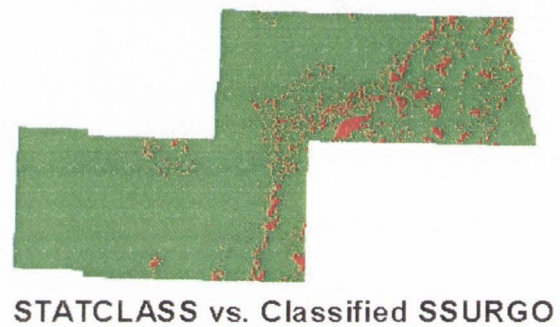
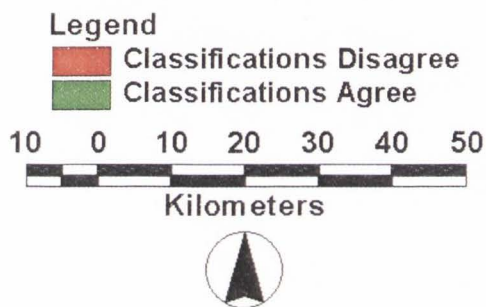
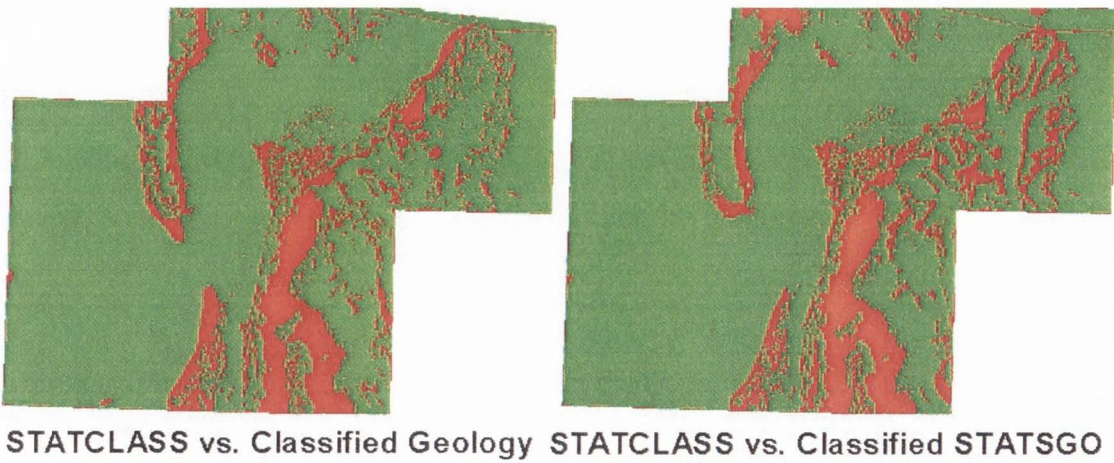


Figure 37. Classification comparison identity grids for the UTTR.

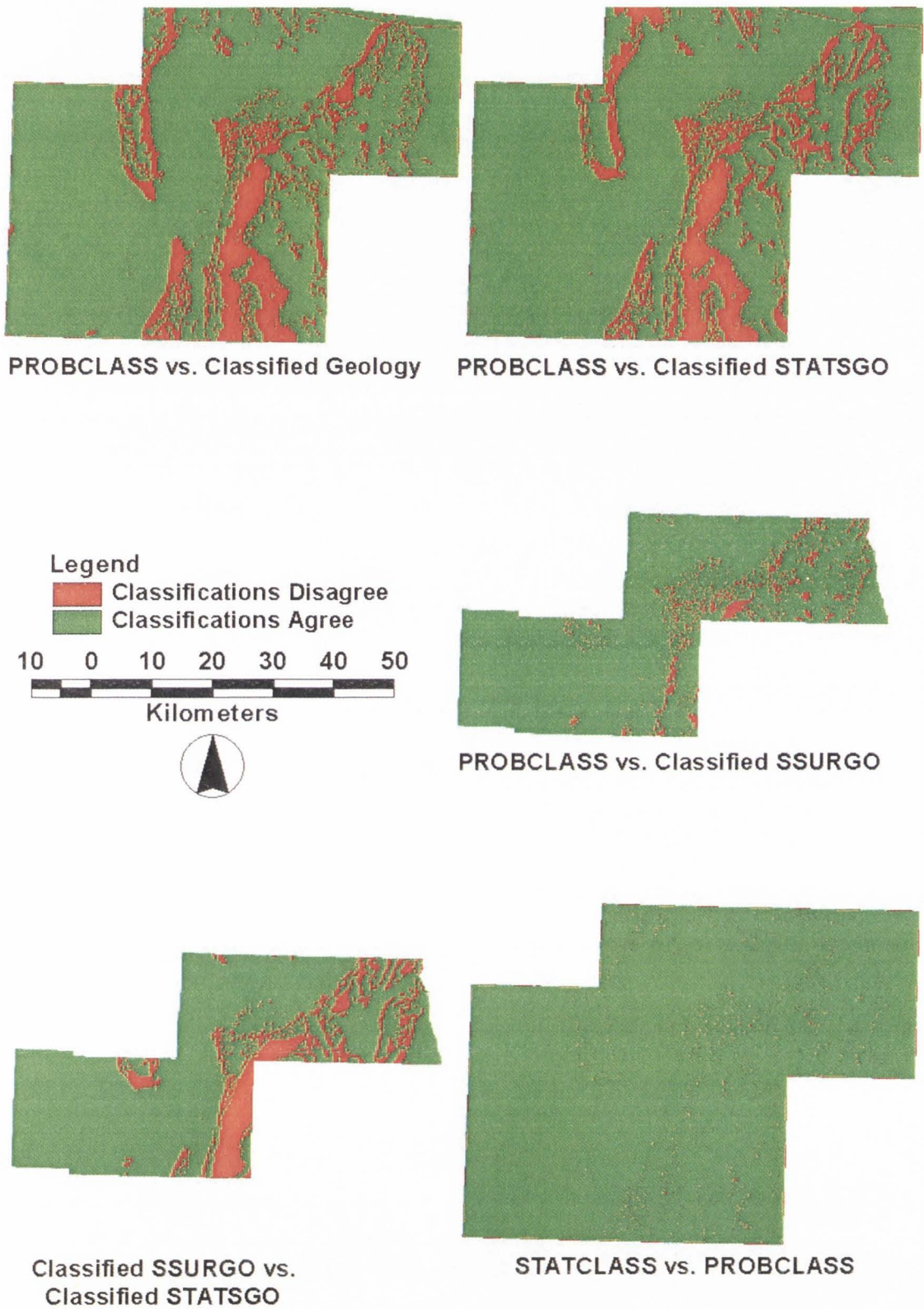


Figure 38. Classification comparison identity grids for the UTTR.



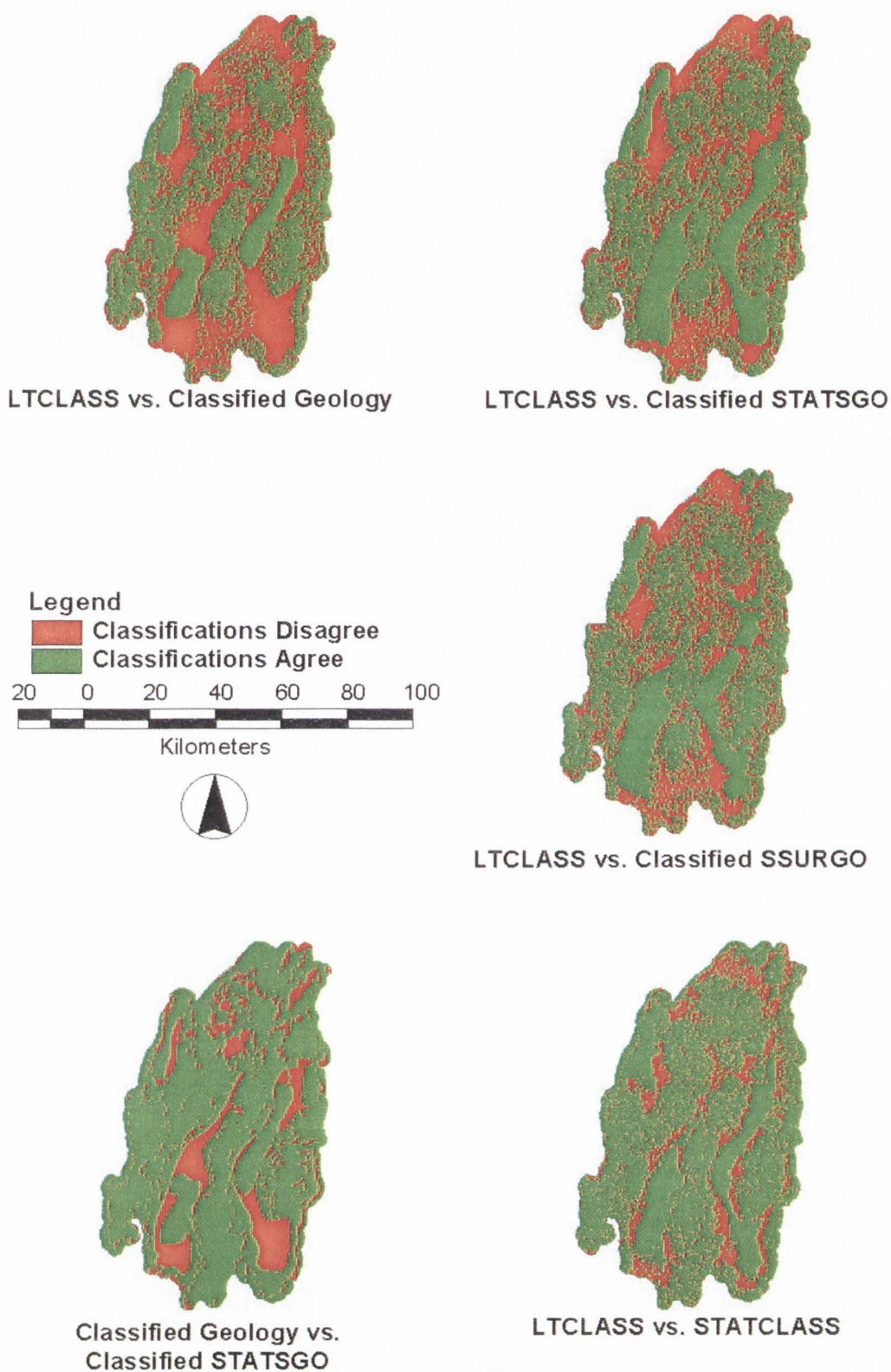


Figure 39. Classification comparison identity grids for MLRA 28b.

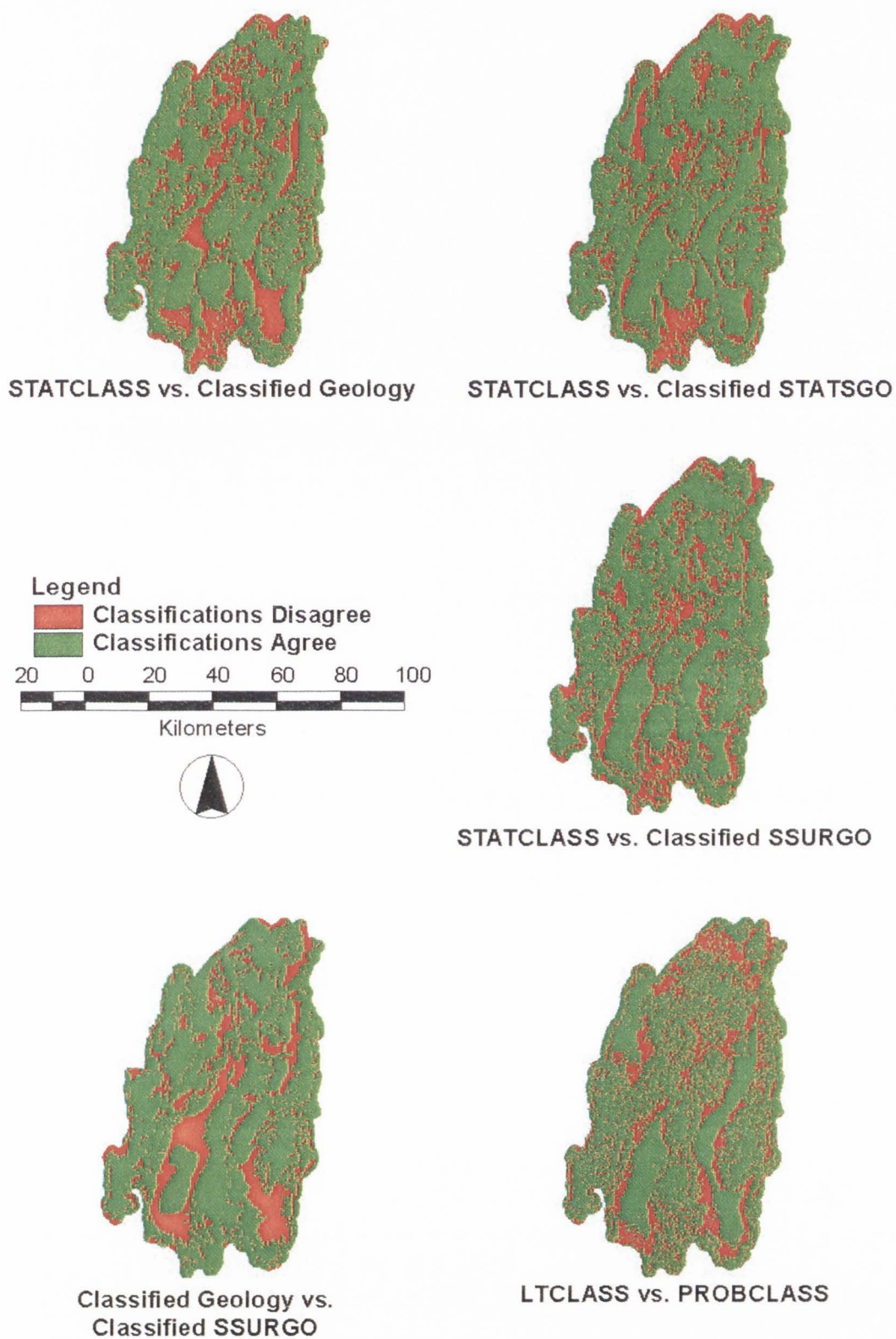


Figure 40. Classification comparison identity grids for MLRA 28b.

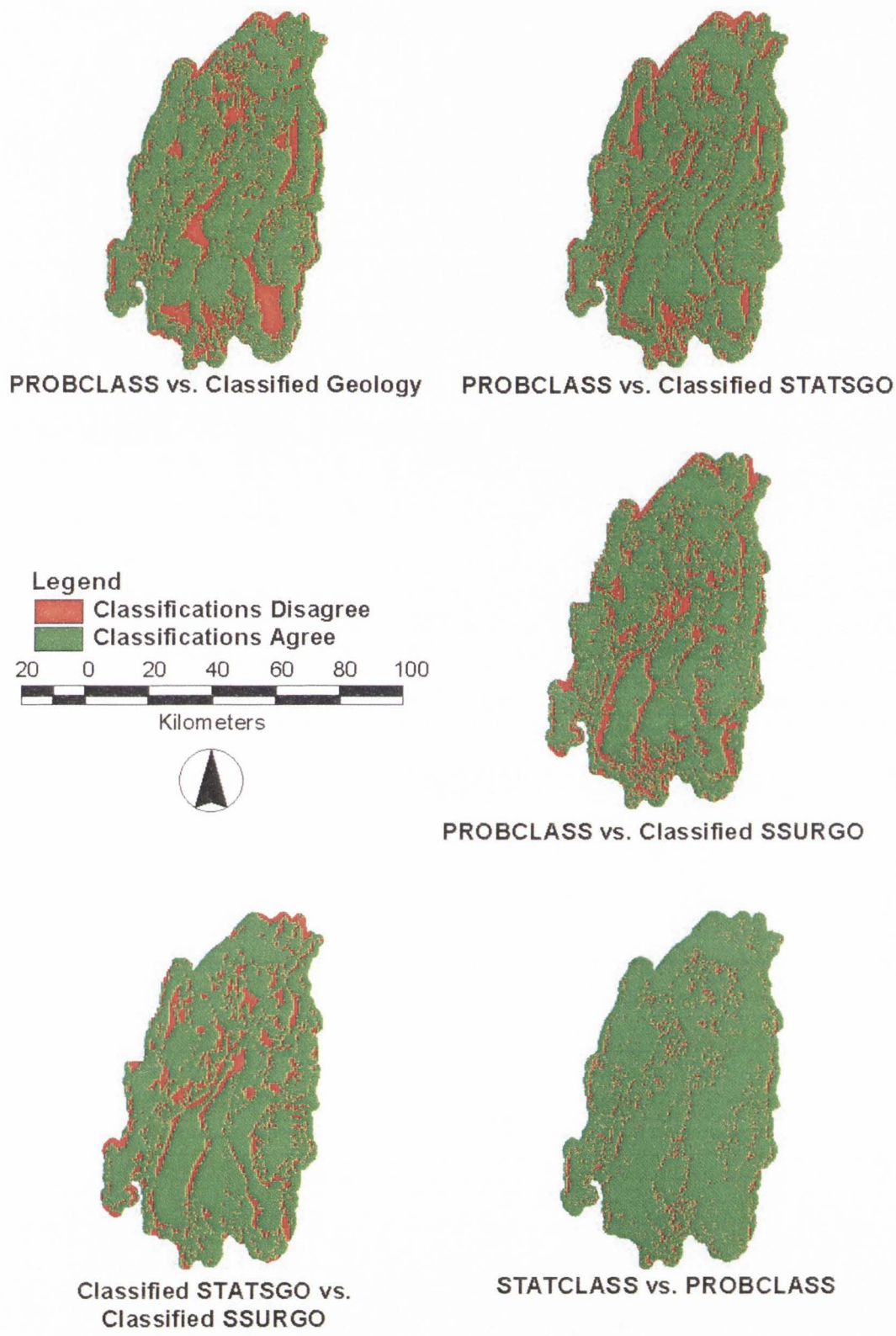


Figure 41. Classification comparison identity grids for MLRA 28b.



In Table III we also see the correlation coefficients between the various reference data for the UTTR. All correlations for Macroterrain Landtype Association classifications were over 80%, the highest correlation being 86.5% between Geology and the STATSGO dataset.

Table IV shows the correlation coefficients for the MLRA 28b study area. The strongest model to reference correlation for this study area was the 0.785 correlation between PROBCCLASS and the STATSGO-based Macroterrain Landtype Association classification. In this case STATSGO had higher correlation coefficients for two of the models than either Geology or SSURGO data, with LTCLASS's highest correlation being with SSURGO. Again, LTCLASS consistently had the lowest correlation coefficients, with a 0.522 correlation with Geology being the lowest value in this study, while in the case of MLRA28b PROBCCLASS had consistently higher coefficients of correlation with the reference data than any of the other models.

In the case of MLRA 28b (Table IV), the highest correlation between classifications of independent data was a 0.797 correlation between SSURGO and STATSGO. The Macroterrain Landtype Association Classification of Geology was most correlated with that of STATSGO, at 0.779.

Table IV. Correlation coefficients for the Central Nevada Basin and Range (MLRA 28b).

	LTCLASS	STATCLASS	PROBCCLASS	Geology	STATSGO	SSURGO
LTCLASS		0.7448	0.6837	0.5224	0.6230	0.6406
STATCLASS	0.7448		0.8949	0.7074	0.7648	0.7262
PROBCCLASS	0.6837	0.8949		0.7482	0.7848	0.7675
Geology	0.5224	0.7074	0.7482		0.7788	0.7251
STATSGO	0.6230	0.7648	0.7848	0.7788		0.7973
SSURGO	0.6406	0.7262	0.7675	0.7251	0.7973	

### *Error Analysis*

The analysis of the accuracy of each model in respect to each class in the Macroterrain Landtype Association Classification, in comparison to the three independent datasets, was performed by the construction of an error matrix for each model output/reference dataset pair. Table V is an error matrix for the slope-based deterministic model, LTCLASS and the Macroterrain Landtype Association Classification for Geology for the UTTR. The highest class agreement in this piecewise assessment is the agreement for the depositional (Basin Floor) class at 94.9%. The highest error of commission (Type I) is 83.3% for the cells that were classified as erosional (Massif) class in the LTCLASS model, but were classified as another Landtype Association in the Geology classification. The highest error of omission (Type II) is 66.9% for cells classified as transitional (Bajada) from the Geology classification, but classified otherwise in the LTCLASS slope model for the UTTR.

Table VI shows the error matrix for LTCLASS when compared to STATSGO data. In this case, the highest agreement is again in the depositional class at 95.7%. The highest Type I error is in the erosional class at 55.4%, and the highest Type II error is in the transitional class at 68.3%. Table VII shows the error matrix for LTCLASS vs. SSURGO data for the UTTR. Once again the highest agreement is in the depositional class at 96.7%, the highest Type I error is in the erosional class at 54.4%, and the highest Type II error is in the transitional class at 45.7%. Tables VIII - X show the error matrices for evaluating the stochastic model, against the three reference datasets for the UTTR.

Table V. LTCLASS vs. Geology error matrix for the UTTR.

Slope Model								
Geology		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	2167325	95506	21604	2284435	94.87	18.10	5.13
	Transitional	410713	318105	231324	960142	33.13	12.59	66.87
	Erosional	2876	25369	275482	303727	90.70	83.27	9.30
	Totals	2580914	438980	528410	3548304	77.81	22.19	22.19

Table VI. LTCLASS vs. STATSGO error matrix for the UTTR.

Slope Model								
STATSGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	2166856	83300	14271	2264427	95.69	19.46	4.31
	Transitional	428760	292697	201773	923230	31.70	15.96	68.30
	Erosional	11860	64084	313864	389808	80.52	55.42	19.48
	Totals	2607476	440081	529908	3577465	77.52	22.48	22.48

Table VII. LTCLASS vs. SSURGO error matrix for the UTTR.

Slope Model								
SSURGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	1221003	40206	999	1262208	96.74	4.79	3.26
	Transitional	60141	145942	62548	268631	54.33	17.13	45.67
	Erosional	292	5817	110601	116710	94.77	54.45	5.23
	Totals	1281436	191965	174148	1647549	89.68	10.32	10.32

Table VIII compares LTCLASS and the Macroterrain Landtype Association Classification of Geology for the UTTR. The highest agreement is in the depositional class at 93.7%. The highest Type I error is in the erosional class at 29.6%, and the highest Type II error is in the transitional class at 46.52%. In Table IX, STATCLASS vs. STATSGO data, the depositional class again has the highest agreement at 94.8%, but in this matrix the highest Type I error falls to the transitional class at 28.6%. The highest Type II error is also in the transitional class at 48.5%. In the error matrix for STATCLASS vs. SSURGO, the highest Type I error is again in the transitional class at 32.2%, but here the highest Type II error falls to the erosional class at 23.4%. Basin floor (depositional) again had the highest correlation, at 95.3%.

Tables XI-XIII show the error matrices between PROBCLASS and the three reference datasets. In Table XI, the highest-class correlation between PROBCLASS and Geology is the depositional class at 92.4%. The highest Type I error is in the erosional class at 28.0% and the highest Type II error is in the transitional class at 43.8%. Table XII, PROBCLASS vs. STATSGO for the UTTR, shows the highest class correlation is in depositional at 93.5%, the highest Type I and Type II errors are both in the transitional class at 32.6% and 45.5%, respectively. In Table XIII, PROBCLASS vs. SSURGO, the highest correlation is once again in depositional at 94.4%. The highest Type I error is 37.1% for the transitional class, and erosional class has the highest Type II error, at 24.8%.

Tables XIV-XXII show the error matrices for the various Macroterrain Landtype Association Classification models as applied to the MLRA 28b study area in comparison



Table VIII. STATCLASS vs. Geology error matrix for the UTTR.

t-Test Model								
Geology		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	2127522	135288	6833	2269643	93.74	15.96	6.26
	Transitional	361102	509813	82442	953357	53.48	23.40	46.52
	Erosional	1155	87751	212694	301600	70.52	29.60	29.48
	Totals	2489779	732852	301969	3524600	80.86	19.14	19.14

Table IX. STATCLASS vs. STATSGO error matrix for the UTTR.

t-Test Model								
STATSGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	2131567	109979	6084	2247630	94.84	17.03	5.16
	Transitional	376758	472110	68182	917050	51.48	28.58	48.52
	Erosional	6122	152083	228758	386963	59.12	19.19	40.88
	Totals	2514447	734172	303024	3551643	79.75	20.25	20.25

Table X. STATCLASS vs. SSURGO error matrix for the UTTR.

t-Test Model								
SSURGO		Depositional	Transitional	Erosional	Totals	Agreement	Type I Error (%)	Type II Error (%)
	Depositional	1203028	59082	98	1262208	95.31	3.17	4.69
	Transitional	39971	215895	12765	268631	80.37	32.18	19.63
	Erosional	5	27352	89353	116710	76.56	11.02	23.44
	Totals	1243004	302329	102216	1647549	91.55	8.45	8.45



Table XI. PROBCCLASS vs. Geology error matrix for the UTTR.

Probability Model								
Geology		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	2110524	167451	6460	2284435	92.39	15.01	7.61
	Transitional	341996	539455	78691	960142	56.18	27.24	43.82
	Erosional	877	94113	208737	303727	68.73	28.04	31.27
	Totals	2453397	801019	293888	3548304	80.57	19.43	19.43

Table XII. PROBCCLASS vs. STATSGO error matrix for the UTTR.

Probability Model								
STATSGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	2117144	141360	5923	2264427	93.50	15.94	6.50
	Transitional	355615	503296	64319	923230	54.51	32.63	45.49
	Erosional	5261	159865	224682	389808	57.64	18.02	42.36
	Totals	2478020	804521	294924	3577465	79.53	20.47	20.47

Table XIII. PROBCCLASS vs. SSURGO error matrix for the UTTR.

Probability Model								
SSURGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	1191532	70587	89	1262208	94.40	2.59	5.60
	Transitional	32724	224283	11624	268631	83.49	37.05	16.51
	Erosional	0	28944	87766	116710	75.20	10.04	24.80
	Totals	1224256	323814	99479	1647549	91.26	8.74	8.74

to the independent geographic datasets. In the error matrices for the deterministic model, LTCLASS, versus the three reference datasets Geology, STATSGO, and SSURGO (Tables XIV-XVI), the correlation is always highest for the depositional class, at 99.3%, 96.1% and 89.0%, respectively; the highest Type I error also consistently falls to the depositional class at 328.7%, 107.6%, and 73.1%, respectively. Type I errors exceeding 100% indicate that more cells were erroneously classified as being depositional (in this case) than the total number of depositional cells that actually existed in the reference dataset. The transitional class is consistently underclassified by the model (Type II error) by 59.6%, 50.3%, and 48.0%, respectively.

In Tables XVII-XIX, the error matrices for STATCLASS vs. the three reference datasets, we begin to see some variation in the high correlation category. In the error matrix for STATCLASS vs. Geology (Table XVII) the highest class-correlation is again in the depositional class at 93.5%, with a high Type I error in the depositional class at 113.9%, and a high Type II error in the erosional class at 40.9%. But in the STATCLASS vs. STATSGO error matrix (Table XVIII), the highest agreement between model and reference class is in the transitional class at 86.3%. The high Type I error for this matrix is 44.3% for the transitional class, and the high Type II error is 37.2% for erosional. In Table XIX, STATCLASS vs. SSURGO for MLRA 28b, the highest class-correlation is again transitional, at 87.6%. The high Type I error for this matrix is in the transitional class at 59.8%, and the high Type II error is 37.0% for the erosional class.

The highest class-correlations for PROBCCLASS in MLRA 28b (Tables XX-XXII) break down the same as they did in the case of STATCLASS (Tables XVII-XIX), with

Table XIV. LTCLASS vs. Geology error matrix for MLRA 28b.

Slope Model								
Geology		Depositional	Transitional	Erosional	Totals	Agreement	Type I Error (%)	Type II Error (%)
	Depositional	552577	3502	257	556336	99.32	328.68	0.68
	Transitional	1724722	1260935	136869	3122526	40.38	31.48	59.62
	Erosional	103819	979410	1411912	2495141	56.59	5.50	43.41
	Totals	2381118	2243847	1549038	6174003	52.24	47.76	47.76

Table XV. LTCLASS vs. STATSGO error matrix for MLRA 28b.

Slope Model								
STATSGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	1123384	43571	1781	1168736	96.12	107.64	3.88
	Transitional	1194462	1304598	128495	2627555	49.65	35.77	50.35
	Erosional	63571	896232	1419012	2378815	59.65	5.48	40.35
	Totals	2381417	2244401	1549288	6175106	62.30	37.70	37.70

Table XVI. LTCLASS vs. STATSGO error matrix for MLRA 28b.

Slope Model								
SSURGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	1304756	159380	1686	1465822	89.01	73.07	10.99
	Transitional	1014550	1200795	95066	2310411	51.97	44.48	48.03
	Erosional	56524	868252	1407694	2332470	60.35	4.15	39.65
	Totals	2375830	2228427	1504446	6108703	64.06	35.94	35.94

Table XVII. STATCLASS vs. Geology error matrix for MLRA 28b.

t-Test Model								
Geology		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	516770	35833	221	552824	93.48	113.85	6.52
	Transitional	628819	2357511	118643	3104973	75.93	33.64	24.07
	Erosional	570	1008809	1460425	2469804	59.13	4.81	40.87
	Totals	1146159	3402153	1579289	6127601	70.74	29.26	29.26

Table XVIII. STATCLASS vs. STATSGO error matrix for MLRA 28b.

t-Test Model								
STATSGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	885432	279606	1641	1166679	75.89	22.35	24.11
	Transitional	258264	2248746	99689	2606699	86.27	44.25	13.73
	Erosional	2463	873801	1477959	2354223	62.78	4.30	37.22
	Totals	1146159	3402153	1579289	6127601	75.27	24.73	24.73

Table XIX. STATCLASS vs. SSURGO error matrix for MLRA 28b.

t-Test Model								
SSURGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	938346	520800	952	1460098	64.27	14.23	35.73
	Transitional	207509	2014972	78604	2301085	87.57	59.79	12.43
	Erosional	302	855111	1458528	2313941	63.03	3.44	36.97
	Totals	1146157	3390883	1538084	6075124	72.62	27.38	27.38



Table XX. PROBCCLASS vs. Geology error matrix for MLRA 28b.

Probability Model								
Geology		Depositional	Transitional	Erosional	Totals	Agreement	Type I Error (%)	Type II Error (%)
	Depositional	513259	41566	326	555151	92.45	107.22	7.55
	Transitional	594658	2222133	300086	3116877	71.29	21.03	28.71
	Erosional	582	613933	1872709	2487224	75.29	12.08	24.71
	Totals	1108499	2877632	2173121	6159252	74.82	25.18	25.18

Table XXI. PROBCCLASS vs. STATSGO error matrix for MLRA 28b.

Probability Model								
STATSGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	866032	298917	3074	1168023	74.15	20.76	25.85
	Transitional	239966	2089200	291420	2620586	79.72	30.09	20.28
	Erosional	2501	489515	1878627	2370643	79.25	12.42	20.75
	Totals	1108499	2877632	2173121	6159252	78.48	21.52	21.52

Table XXII. PROBCCLASS vs. SSURGO error matrix for MLRA 28b.

Probability Model								
SSURGO		Depositional	Transitional	Erosional	Totals	Agreement (%)	Type I Error (%)	Type II Error (%)
	Depositional	918566	540257	5835	1464658	62.72	12.97	37.28
	Transitional	189623	1880770	238261	2308654	81.47	42.64	18.53
	Erosional	308	444234	1882524	2327066	80.90	10.49	19.10
	Totals	1108497	2865261	2126620	6100378	76.75	23.25	23.25



agreements of 92.4% for depositional, and 79.7%, and 81.5% for transitional in the comparisons to Geology, STATSGO, and SSURGO, respectively. In the error matrix for PROBCCLASS vs. Geology (Table XX), the highest Type I error is 107.2% for the depositional class, and the high Type II error is 28.7% for the transitional class. The high Type I error for Table XXI (PROBCCLASS vs. STATSGO) falls to the transitional class at 30.1%, and the high Type II error is 25.9% for the depositional class. In Table XXII (PROBCCLASS vs. SSURGO), the highest Type I error is 42.6% in the transitional class, and the high Type II error is 37.3% for the depositional class.

### *Performance Analysis*

The final method for assessing the model outputs against the independent geographical datasets was to analyze the actual performance of the models versus the accuracy one might expect from random chance. To this end, Kappa statistics were calculated for each model output/reference dataset pair (Campbell, 1987). Table XXIII presents a summary of the Kappa statistics generated for the UTTR. In this analysis, all three models performed best in comparison to the SSURGO data, second-best in comparison to the Geology classification, and marginally worse for the Macroterrain

Table XXIII. Kappa statistics for the UTTR.

	Geology	STATSGO	SSURGO
LTCLASS	0.5429	0.5420	0.7268
STATCLASS	0.6026	0.5861	0.7820
PROBCCLASS	0.6007	0.5861	0.7784

Landtype Association classification for the STATSGO data. The single best model performance was STATSCCLASS vs. SSURGO data, at 78.2% better than can be expected by random chance. The worst model performance for the UTTR was LTCLASS vs. STATSGO, that performed 54.2% better than random. Table XXIV presents a summary of the Kappa statistics calculated for the MLRA 28b study area. In this analysis, one finds that the performance of the models versus reference datasets was not as consistent as was the case in the UTTR study area. Here, though LTCLASS did perform marginally better for SSURGO data than it did for STATSGO, both STATSCCLASS and PROBCLASS performed better in comparison to STATSGO than for any other independent dataset. The highest performance for the MLRA 28b study area was PROBCLASS vs. STATSGO at 65.9% better than random chance. The lowest Kappa statistic was seen for LTCLASS vs. Geology, at 29.8% better than random chance.

Table XXIV. Kappa statistics for MLRA 28b.

	Geology	STATSGO	SSURGO
LTCLASS	0.2977	0.4420	0.4673
STATSCCLASS	0.5106	0.6069	0.5767
PROBCLASS	0.5836	0.6591	0.6398

## DISCUSSION

### *Model Assessment*

By every method of analysis applied in this study, all three models performed better when applied to the UTTR than they did when applied to MLRA 28b. This is likely due to the greater homogeneity of the UTTR's landscape, wherein over 75% of the area is classified as Basin Floor by all three independent geographical datasets; whereas the landscape of MLRA 28b is much more heterogeneous, and the three Macroterrain Landtype Association classes are much more evenly represented. This conclusion is further suggested by the fact that the highest class-agreement in 7 out of 9 total error matrices for the UTTR (Tables V-XIII) falls to the Basin Floor (depositional) class. This is only the case for 5 out of 9 error matrices for MLRA 28b (Tables XIV-XXII), three of which apply to LTCLASS (Tables XIV-XVI), where the over-representation of the Basin Floor class is evidenced by high Type I errors for all three comparisons. While this landscape-based discrepancy in model performance should be noted, as it may be an issue in applying these methods to different landscapes, it does not appear to have given a performance advantage to any one model over the other two.

Based on the three methods of performance analysis applied in this study, the model which best classifies a landscape's slope data into Macroterrain Landtype Associations is the probability-based stochastic model, PROBCCLASS. This model's average Kappa statistic for its performance against all three independent reference datasets over both the UTTR and MLRA 28b study areas is 0.6413. The average Kappa statistic for STATCLASS is 0.6108, and for the slope-based deterministic model,

LTCLASS, the average Kappa statistic is only 0.5031. Based solely upon these statistics, and the correlative error and agreement statistics from which Kappa is derived, one would expect a recommendation that future users apply the PROBCCLASS model to their Macroterrain Landtype Association classifications. But a thorough analysis of the performance must also take into account the costs of applying a particular method, as well as the benefits.

PROBCCLASS, while it does out-perform STATCLASS by some margin, is an iterative model that takes a considerable amount of time to prepare and run. While STATCLASS takes about the same amount of preparation time (2 to 5 hours for digitizing training sites, *etc.*) as PROBCCLASS, the average run time for STATCLASS was just over one hour, versus nearly four days for a set of 100 iterations in PROBCCLASS. When classifying large landscape areas, memory space may also prove to be an issue, as the execution of PROBCCLASS requires greater disk space than STATCLASS by an amount proportionate to the number of iterations. LTCLASS requires no model preparation other than filling in DEM sinks when desired, and less disk space than either of the stochastic models. Run time for LTCLASS averaged only about twenty minutes, much shorter than the other two models. Furthermore, LTCLASS required little expertise to run, asking only that the user input reasonable slope thresholds for the class delineation; whereas considerable technical and geomorphic and/or ecologic knowledge was required in the preparation for and execution of STATCLASS and PROBCCLASS.

LTCLASS bore other advantages, owing to its nature as a deterministic model. Unlike stochastic models that are, in theory, unbiased models, deterministic models such



as LTCLASS are goal-oriented. Such models can be fine-tuned to apply well to a small area in ways that stochastic models cannot. For example, an examination of the error matrices for LTCLASS (Tables V-VII) shows that the error of commission is consistently highest for the Massif (erosional) class, whereas the error of omission is consistently highest for the Bajada (transitional) class. This would indicate that Massif is being over-classified, and Bajada is being under-classified. Thus, the model LTCLASS's classification could be adjusted to fit the reference data better by raising the slope threshold which discriminates between Massif and Bajada. This would decrease the map area classed as Massif, and increase the area classed as Bajada, without affecting the Basin Floor class. Whether this "tuneability" is a desirable feature is dependent upon the users' need for an "accurate" model versus an "unbiased" one. Unfortunately, the ability to fine-tune a model does not necessarily apply to large study areas. The over-classing of Massif in the UTTR is a direct result of the lowering of the slope threshold to match the needs of applying the same criteria in the MLRA 28b study area. An adjustment to the criteria to improve the performance for the UTTR would considerably degrade LTCLASS's performance for MLRA 28b.

### *Conclusions*

Based on the analyses of the models' performance, and the above *ad hoc* assessment of the various costs and benefits of running the three Macroterrain Landtype Association Classification models, it is recommended that for most applications in an ecological classification setting, that STATCLASS be the model applied. While it was marginally outperformed by PROBCCLASS in an overall average (STATCLASS actually



had a higher average Kappa statistic for the UTTR than did PROBCCLASS) its advantages in speed and disk space appear to outweigh this minor disadvantage. Where a definitive measure of the confidence of a classification is required, probability grid generated by PROBCCLASS is far superior to the *t*-value grids generated by STATCLASS in terms of ease-of-interpretation, and should be considered as the recommended application. The only circumstances in which LTCLASS would be recommended are those in which a “quick and dirty” assessment of the Landtype Associations is desired, rather than a full classification; or any situation in which slope-thresholds are required as classification criteria.

#### *Suggestions for Further Work*

In the years since these models were first developed, other spatial classification methods such as Classification and Regression Tree (CART) analysis have gained popularity. Other methods, such as fuzzy-logic classification, were available at the time of this study, but were deemed to be too complicated to implement for the time frame of the HAFB TES project. It is suggested that other such methods be explored to determine their performance in relation to the methods examined in this study.

It is further suggested that additional assessment of the performance of PROBCCLASS versus that of STATCLASS may reveal a greater disparity than that measured in this study. This is because the performance of STATCLASS is largely dependent upon a single randomly sampled population from the training data. There is a chance that the random populations generated in the course of this study better represented the Macroterrain Landtype Associations than may be expected on average.

An averaging of the assessment statistics from further iterations of STATCLASS may show that PROBCCLASS performs much better than is suggested in this study (relative to the performance of STATCLASS).

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**APPENDICES**



Appendix A: AML code for LTCLASS

```

/* LTCLASS.AML
/* Frank L. Dougher                      Nov. 11, 1998
/* This aml produces LT masks from entered parameters
/*
/* Run aml once for each class above basal class.
/* Combine Landtype masks with an addition statement.
/* e.g. output = (landtype02 + landtype03 + 1)

&type 'LISTING GRIDS FOR THIS DIRECTORY...\''
lg

&type '\\'

/* query user for operational variables
&sv slope := [response 'ENTER THE DEGREE-SLOPE GRID <MOASLOPE>'
moaslope]
&sv flowd := [response 'ENTER THE FLOW DIRECTION GRID <MOAFLOWD>'
moaflowd]
&sv degs := [response 'ENTER SLOPE BREAK POINT IN DEGREES']
&sv slpname := [response 'ENTER NAME OF SLOPE MASK']
&sv ltname := [response 'ENTER NAME OF LANDFORM MASK']

&type '\GENERATING SLOPE MASK'

/* remove existing model output
&if [exists %slpname% -grid] &then kill %slpname% all

/* conditional statement to create slope mask
%slpname% = con((%slope% >= %deg%), 1, 0)

&type '\GENERATING LANDTYPE MASK'

/* remove existing model output
&if [exists %ltname% -grid] &then kill %ltname% all

/* watershed function imposes class-superposition
%ltname% = watershed(%flowd%, %slpname%)

&return

```

## Appendix B: AML code for STATCLASS

```

/* STATCLASS.AML
/* Frank L. Dougher                                Feb. 8, 1999
/*
/* To be run in GRID.
/*
/* This AML will classify a grid into a chosen number of classes
/* by T-test comparison of Std. Dev. and Means of samples of
/* of class archetypes.
/*
/* Running this aml with ANY argument will force the running mode
/* into a dumb-terminal mode for non-Xwindows terminals.

/* argument sets dumb-terminal mode
&args no_menu
&if [null %no_menu%] &then &term 9999
&severity &error &routine exit

/* intro statement
&type
&type
&type
&type This is STATCLASS. This AML will classify an image by statistical
&type comparison to class-type images.\The image to be classified will have
&type the focal mean and focal standard deviation calculated, and then
&type compared to masked images of the class-types.\This program must reside
&type in the same directory as your data and RANDSAMP.AML\If you do not have
&type RANDSAMP.AML, please quit and get it before running STATCLASS.AML.\Thank
&type You.
&type
&type
&type
&sv goon = [query 'Shall we go on' .true.]
&if ^ %goon% &then &stop

/* get the input grids and variables *****
/*

/* Select input grid from pop-up menu.
/*
&type Please select the grid to be classified
&type &if [null %no_menu%] &then &sv in_grid = [getgrid *]
&type &else
&type &do
&type &lg
&type &sv in_grid = [response 'in_grid is ']
&type &end
&type

/* Enter the output grid name, and check to see if it already exists.
/*
&label getout
&sv out_grid = [response 'What would you like to call your classified
&type output grid' output_c]
&type &if [exists %out_grid% -grid] &then &type %out_grid% exists.
&type &if [exists %out_grid% -grid] &then &goto getout
&type

/* Prompt user to save t-value output, enter the output grid name,

```

```

/* and check to see if it already exists.
/*
&sv doval = [query 'Do you want a T-value output grid' .false.]
&type
&if %doval% &then
    &do
        &label getval
        &sv out_val = [response 'What would you like to call your T-value
output grid' output_t]
        &if [exists %out_val% -grid] &then &type %out_val% exists.
        &if [exists %out_val% -grid] &then &goto getval
    &end
&type

/* Enter width of square focal window.
/*
&sv win_width = [response 'What focal width (square) do you want to use?
Odd number please' 7]
&type

/* Enter N-value.
/*
&sv samp_n = [response 'How many samples 'N' do you want taken from
each class' 50]
&type

/* Select %num_class%# of class-type grids from pop-up menu.
/*
&sv num_class = [response 'How many classes will this model produce']
&do count = 1 &to %num_class% &by 1
    &type Please select class-type%count%
    &if [null %no_menu%] &then &sv class%count% = [getgrid *]
    &else
        &do
            lg
            &sv class%count% = [response 'Class' ]
        &end
    &type
&end

/* Prompt user to save mean and standard deviation output, enter the
/* output grid names, and check to see if they already exist.
/*
&sv gotem = [query 'Do you already have a mean and standard deviation'
.false.]
&if %gotem% &then &do
    &sv saveem = .true.
&end
&else &sv saveem = [query 'Do you want to save the focal mean and
standard deviation at the end of the program' .false.]
&if %saveem% &then
    &do
        &label getmean
        &sv out_mean = [response 'Name of focal mean output' out_mean]
        &if ^ %gotem% &then &do
            &if [exists %out_mean% -grid] &then &type %out_mean% exists.
            &if [exists %out_mean% -grid] &then &goto getmean
        &end
    &end

```



```

    &label getstdv
    &sv out_stdv = [response 'Name of focal standard deviation output'
out_stdv]
    &if ^ %gotem% &then &do
        &if [exists %out_stdv% -grid] &then &type %out_stdv% exists.
        &if [exists %out_stdv% -grid] &then &goto getstdv
    &end
    &type
&end

/* Start of calculations *****
/*

/* Focal Mean & Standard Deviation
/*
&if ^ %gotem% &then &do
    &type Calculating Focal Mean
    &if ^ %saveem% &then &sv out_mean = [SCRATCHNAME]
    %out_mean% = focalmean(%in_grid%, rectangle, %win_width%, %win_width%,
nodata)
    &type
    &type Calculating Focal Standard Deviation
    &if ^ %saveem% &then &sv out_stdv = [SCRATCHNAME]
    %out_stdv% = focalstd(%in_grid%, rectangle, %win_width%, %win_width%,
nodata)
    &type
&end

/* Class Statistics
/*
&type Running Stats on Classes
&sv file_unit = [open %out_grid%.log openstatus -write]
&do count = 1 &to %num_class% &by 1
    &type Class%count%:
    &sv temp_class = [value class%count%]
    &sv temp_n = %samp_n%
    &sv nmintest = .false.
    &sv nmincount = 1
    &do &until %nmintest% or %nmincount% >= 10
        &r randsamp.aml %temp_class% %temp_n% %win_width%
        &sv c%count%_mean = %.statmean%
        &sv c%count%_stdv = %.statstdv%
        &sv c%count%_n = %.statn%
&echo &on
        nmin_number = scalar(sqr(2.54 * %.statstdv%)) /* 2.54 is the t-value
for 95% confidence
        nmin_denom = scalar(0.05 * %.statmean%) /* 0.05 is remainder for
100% - 95%
        nmin = scalar(int((nmin_number / nmin_denom) + .5))
        &sv nmin = [show nmin]
        &sv nmin = [min 100 %nmin%]
        &if %nmin% <= [value c%count%_n] &then &sv nmintest = .true.
        &else &do
            &type [quote Running again. c%count%_n = [value c%count%_n], n_min
= %nmin%]
            &sv temp_n = %nmin%
        &end
&echo &off

```

```

        &sv nmincount = %nmincount% + 1
    &end
    &sv writestat = [write %file_unit% [quote class%count%_mean = [value
c%count%_mean]]]
    &sv writestat = [write %file_unit% [quote class%count%_stdv = [value
c%count%_stdv]]]
    &sv writestat = [write %file_unit% [quote class%count%_n = [value
c%count%_n]]]
    &end
    &sv closestat = [close %file_unit%]
    &type

/* Create T-value grids
/*
&type Creating T-value grids:
&do count = 1 &to %num_class% &by 1
    &type Class %count%
    &sv c_mean = [value c%count%_mean]
    &sv c_stdv = [value c%count%_stdv]
    &sv c_n = [value c%count%_n]
    &sv t%count%_out = [SCRATCHNAME]
    &sv temp_t = [value t%count%_out]
DOCELL
    sig1sq = scalar(sqr(%out_stdv%))
    sig2sq = scalar(sqr(%c_stdv%))
    m1val = scalar(%out_mean%)
    m2val = scalar(%c_mean%)
    n1val = scalar(sqr(%win_width%) - 1)
    n2val = scalar(%samp_n% - 1)
    numer = scalar(abs(m1val - m2val))
    denom = scalar(sqrt((sig1sq / n1val) + (sig2sq / n2val)))
    %temp_t% = (numer / denom)
END
&end
&type

/*****
/* Classifying the Image
/*
&type Classifying Image
&sv end = %num_class% - 1
&if %end% < 1 &then &call exit
/*%out_grid% = (%t1_out% / %t1_out%)
DOCELL
    c_num = scalar(0)
    &sv tmp_a = [value t1_out]
    o_val = scalar(%tmp_a%)
    &do count = 1 &to %end% &by 1
        &sv countb = %count% + 1
        &do &while %countb% <= %num_class%
            &sv tmp_a = [value t%count%_out]
            &sv tmp_b = [value t%countb%_out]
            if (%tmp_a% <= %tmp_b% & %tmp_a% <= o_val)
                begin
                    c_num = scalar(%count%)
                    o_val = scalar(%tmp_a%)
                end
            else if (%tmp_b% <= o_val)

```

```

        begin
            c_num = scalar(%countb%)
            o_val = scalar(%tmp_b%)
        end
        &sv countb = %countb% + 1
    &end
    &end
    %out_grid% = (c_num)
    &if %doval% &then
        %out_val% = o_val
    END
    &type

/* *****

/* Clean up the scratch files.
/*
&if ^ %saveem% &then &call killms
&do count = 1 &to %num_class% &by 1
    &sv killme = [value t%count%_out]
/* kill %killme% all
    &sv outtname = %out_val%_%count%
    rename %killme% %outtname%
&end

/* Output final message and quit.
/*
&type Process all done. Your output is in %out_grid%.
&type

&return

/*-----routines-----

/* Kill the output grids for focal mean and standard deviation
/*
&routine killms
    kill %out_mean% all
    kill %out_stdv% all
&return

/* Exit from an error condition.
/*
&routine exit
    &type ERROR encountered in randsamp.aml: Bailing out
    &stop

```

Appendix C: AML code for *RANDSAMP.AML*

```

/* RANDSAMP.AML
/* Frank L. Dougher                                Feb. 3, 1999
/*
/* modified from:
/* RANDPOINT.AML
/* Thad Tilton                                    Jan. 8, 1997
/*
/* To be run in GRID.
/*
/* This AML will sample from a grid at a number of random points
/* defined by the user.
/* User defines the number of points, the grid to be sampled from,
/* and an output file (if desired).

&args sampgrd num_pts winsize
&severity &error &routine exit

/* First, get the arguments.

&if [null %sampgrd%] &then
  &do
    &type Usage: &r RANDSAMP <in_grid> <number_of_samples> {window_width}
    &return
  &end

&if ^ [exists %sampgrd% -grid] &then
  &do
    &type %sampgrd% does not exist.
    &return
  &end

&if [type %num_pts%] ne -1 &then
  &do
    &type %num_pts% must be an integer.
    &return
  &end

&if ^ [null %winsize%] &then
  &if [type %winsize%] ne -1 &then
    &do
      &type %winsize% must be an integer.
      &return
    &end

/* Next, the required parameters are obtained and the appropriate
variables
/* are calculated ...

&describe %sampgrd%
&sv xmin = %GRD$XMIN%
&sv ymin = %GRD$YMIN%
&sv xdiff = %GRD$XMAX% - %GRD$XMIN%
&sv ydiff = %GRD$YMAX% - %GRD$YMIN%
&sv i = 1

/* Prompt user to see if they want to use focalmeans in their sampling.
&if [null %winsize%] &then &sv dofocal = [query 'Do you wish to use
focal window means in your sampling' .false.]

```



```

&else
  &do
    &if %winsize% ^= 1 &then &sv a = 2
    &else &sv a = 1
    &goto start
  &end

&if %dofocal% &then &call focalsamps
&else &sv a = 1

/* Now, for NUM_PTS iterations: generate random points, sample grid
value,
/* test for NODATA, and record good values.
&label start
&type
/*&do i = 1 &to %num_pts% &by 1
  &label sample
  &call rand_pt
  &if %a% = 2 &then
    &do
      &sv foc_tot = [calc %winsize% * %winsize%]
      &sv dx = %GRD$DX%
      &sv wmo = %winsize% - 1
      &sv dp = [calc %wmo% / 2]
      &sv winsampt = 0
      &do dpx = -%dp% &to %dp%
        &do dpy = -%dp% &to %dp%
          &sv dgx = [calc %dpx% * %dx%]
          &sv dgy = [calc %dpy% * %dx%]
          &sv x = %x-coord% + %dgx%
          &sv y = %y-coord% + %dgy%
          &sv wsamp = [show cellvalue %sampgrd% %x% %y%]
          &if [type %wsamp%] = 1 &then
            &do
              &sv winsampt = 0
              &goto sample
            &end
          &sv winsampt = %winsampt% + %wsamp%
        &end
      &end
      &sv sample%i% = [calc %winsampt% / %foc_tot%]
    &end
  &else &if %a% = 1 &then
    &sv sample%i% [show cellvalue %sampgrd% %x-coord% %y-coord%]
    &if [type [value sample%i%]] = 1 &then &goto sample
    &sv i = %i% + 1
  /*&end
&if %i% le %num_pts% &then &goto sample

/* Caluate statistics for sample set.
&sv sampsum = 0
&sv i = 1
&do &while %i% <= %num_pts%
  &sv sampi = [value sample%i%]
  &sv sampsum = %sampsum% + %sampi%
  &sv i = %i% + 1
&end

```

```

&sv mean = [calc %sampsum% / %num_pts%]

&sv diffsum = 0
&sv i = 1
&do &while %i% <= %num_pts%
    &sv sampo = [value sample%i%]
    dif = scalar(sqrt(%sampo% - %mean%))
    &sv diff = [show dif]
    &sv diffsum = %diffsum% + %diff%
    &sv i = %i% + 1
&end

&sv vari = [calc %diffsum% / %num_pts%]
sd = scalar(sqrt(%vari%))
&sv std_dev = [show sd]

/* If the user specified an output filename, print to that file.
/* Otherwise print to screen.

&call out

&return

/*-----routines-----

/* prompt user for size of focal window.
&routine focalsamps
    &sv a = 2
    &sv winsize = [response 'What focal width (square) do you want to use?
        Odd number please' 3]
&return

/* a random grid is generated containing random X and Y coordinates in
the VAT
/* within the range specified
&routine rand_pt
xc = scalar(rand() * %xdiff% + %xmin%)
    &sv x-coord [show xc]
yc = scalar(rand() * %ydiff% + %ymin%)
    &sv y-coord [show yc]
&return

/* Print output to screen.
&routine out
    &type
    &type *****SAMPLE*****
    &type MEAN: %mean%
    &type STD.DEV.: %std_dev%
    &type N: %num_pts%
    &type
    &type *****GRID*****
    &type GRID MEAN: %GRD$MEAN%
    &type GRID STD.DEV. %GRD$STDV%
    &type
/* output global variables for statclass.aml
&sv .statmean = %mean%
&sv .statstdv = %std_dev%
&sv .statn = %num_pts%

```

```
&sv sampi = 00
&return

/* Exit from an error condition.
&routine exit
    &type ERROR encountered in randsamp.aml: Bailing out
&stop
```

## Appendix D: AML code for PROBCCLASS

```

/* RUNLOOP.AML
/* Frank L. Dougher                      Mar. 8, 2002
/*
/* This AML runs ITERCLASS.AML for the number of iterations
/* specified by the variable count.
/*
&sv count = 1
&do &while %count% <= 100
  &sv countstring = %count%
  &if %count% <= 99 &then &sv countstring = 0%countstring%
  &if %count% <= 9 &then &sv countstring = 0%countstring%
  &r iterclass.aml nr07c%countstring%
  &sv count = %count% + 1
&end

```

```

/* ITERCLASS.AML
/* Frank L. Dougher                      Mar. 8, 2002
/*
/* modified from:
/* STATCLASS.AML
/* Frank Dougher                        Feb. 8, 1999
/*
/* To be run in GRID.
/*
/* This AML will classify a grid into a chosen number of classes
/* by T-test comparison of Std. Dev. and Means of samples of
/* of class archetypes.
&args no_menu
grid
&if [null %no_menu%] &then &term 9999
&severity &error &routine exit

/* get the input grids and variables *****
/*
/* Select input grid from pop-up menu.
/*
/*&type Please select the grid to be classified
  &if [null %no_menu%] &then &sv in_grid = [getgrid *]
  &else
    &do
      /*      lg
        &sv in_grid = nr_slope
      &end
    /*&type

/* Enter the output grid name, and check to see if it already exists.
/*
&label getout
&sv out_grid = %no_menu%
&if [exists %out_grid% -grid] &then &type %out_grid% exists.
&if [exists %out_grid% -grid] &then &goto getout
/*&type

```



```

/* Prompt user to save t-value output, enter the output grid name,
/* and check to see if it already exists.
/*
&sv doval = .false.
/*&type
&if %doval% &then
  &do
    &label getval
    &sv out_val = [response 'What would you like to call your T-value
output grid' output_t]
    &if [exists %out_val% -grid] &then &type %out_val% exists.
    &if [exists %out_val% -grid] &then &goto getval
  &end
&type

/* Enter width of square focal window.
/*
&sv win_width = 7
/*&type

/* Enter N-value.
/*
&sv samp_n = 50
/*&type

/* Select %num_class%# of class-type grids from pop-up menu.
/*
&sv num_class = 3
&sv class1 = sampval
&sv class2 = sampbaj
&sv class3 = sampmas

/* Prompt user to save mean and standard deviation output, enter the
/* output grid names, and check to see if they already exist.
/*
&sv gotem = .true.
&if %gotem% &then &do
  &sv saveem = .true.
&end
&if %saveem% &then
  &do
    &label getmean
    &sv out_mean = area30_07m
    &if ^ %gotem% &then &do
      &if [exists %out_mean% -grid] &then &type %out_mean% exists.
      &if [exists %out_mean% -grid] &then &goto getmean
    &end
    &label getstdv
    &sv out_stdv = area30_07s
    &if ^ %gotem% &then &do
      &if [exists %out_stdv% -grid] &then &type %out_stdv% exists.
      &if [exists %out_stdv% -grid] &then &goto getstdv
    &end
  &do
    &type
  &end
&end

```

```

/* Start of calculations *****
/*

/* Focal Mean & Standard Deviation
/*
&if ^ %gotem% &then &do
/* &type Calculating Focal Mean
  &if ^ %saveem% &then &sv out_mean = [SCRATCHNAME]
  %out_mean% = focalmean(%in_grid%, rectangle, %win_width%, %win_width%,
nodata)
/* &type
/* &type Calculating Focal Standard Deviation
  &if ^ %saveem% &then &sv out_stdv = [SCRATCHNAME]
  %out_stdv% = focalstd(%in_grid%, rectangle, %win_width%, %win_width%,
nodata)
  &type
&end

/* Class Statistics
/*
/*&type Running Stats on Classes
/*&sv file_unit = [open %out_grid%.log openstatus -write]
&do count = 1 &to %num_class% &by 1
/* &type Class%count%:
  &sv temp_class = [value class%count%]
  &sv temp_n = %samp_n%
/* &sv nmintest = .false.
/* &sv nmincount = 1
/* &do &until %nmintest% or %nmincount% >= 10
  &r randsamp.aml %temp_class% %temp_n% %win_width%
  &sv c%count%_mean = %.statmean%
  &sv c%count%_stdv = %.statstdv%
  &sv c%count%_n = %.statn%
/*   nmin_number = scalar(sqr(2.54 * %.statstdv%)) /* 2.54 is the t-
value for 95% confidence
/*   nmin_denom = scalar(0.05 * %.statmean%) /* 0.05 is remainder for
100% - 95%
/*   nmin = scalar(int((nmin_number / nmin_denom) + .5))
/*   &sv nmin = [show nmin]
/*   &sv nmin = [min 100 %nmin%]
/*   &if %nmin% <= [value c%count%_n] &then &sv nmintest = .true.
/*   &else &do
/*     &type [quote Running again. c%count%_n = [value c%count%_n],
n_min = %nmin%]
/*     &sv temp_n = %nmin%
/*   &end

/*&echo &off
/*   &sv nmincount = %nmincount% + 1
/*   &end
/*   &sv writestat = [write %file_unit% [quote class%count%_mean = [value
c%count%_mean]]]
/*   &sv writestat = [write %file_unit% [quote class%count%_stdv = [value
c%count%_stdv]]]

```

```

/* &sv writestat = [write %file_unit% [quote class%count%_n = [value
c%count%_n]]]
&end
/*&sv closestat = [close %file_unit%]
/*&type

/* Create T-value grids
/*
/*&type Creating T-value grids:
&do count = 1 &to %num_class% &by 1
/* &type Class %count%
    &sv c_mean = [value c%count%_mean]
    &sv c_stdv = [value c%count%_stdv]
    &sv c_n = [value c%count%_n]
    &sv t%count%_out = [SCRATCHNAME]
    &sv temp_t = [value t%count%_out]
DOCELL
    sig1sq = scalar(sqr(%out_stdv%))
    sig2sq = scalar(sqr(%c_stdv%))
    m1val = scalar(%out_mean%)
    m2val = scalar(%c_mean%)
    n1val = scalar(sqr(%win_width%) - 1)
    n2val = scalar(%samp_n% - 1)
    numer = scalar(abs(m1val - m2val))
    denom = scalar(sqrt((sig1sq / n1val) + (sig2sq / n2val)))
    %temp_t% = (numer / denom)
END
&end
/*&type

/*****
/* Classifying the Image
/*
/*&type Classifying Image
&sv end = %num_class% - 1
&if %end% < 1 &then &call exit
/*out_grid% = (%t1_out% / %t1_out%)
DOCELL
    c_num = scalar(0)
    &sv tmp_a = [value t1_out]
    o_val = scalar(%tmp_a%)
    &do count = 1 &to %end% &by 1
        &sv countb = %count% + 1
        &do &while %countb% <= %num_class%
            &sv tmp_a = [value t%count%_out]
            &sv tmp_b = [value t%countb%_out]
            if (%tmp_a% <= %tmp_b% & %tmp_a% <= o_val)
                begin
                    c_num = scalar(%count%)
                    o_val = scalar(%tmp_a%)
                end
            else if (%tmp_b% <= o_val)
                begin
                    c_num = scalar(%countb%)
                    o_val = scalar(%tmp_b%)
                end
            end
            &sv countb = %countb% + 1
        &end
    &end

```

```

&end
  %out_grid% = (c_num)
  &if %doval% &then
    %out_val% = o_val
END
/*&type
/*****

/* Clean up the scratch files.
/*
&if ^ %saveem% &then &call killms
&do count = 1 &to %num_class% &by 1
  &sv killme = [value t%count%_out]
  kill %killme% all
/*  &sv outtname = %out_val%_%count%
/*  rename %killme% %outtname%
&end

/* Output final message and quit.
/*
&type Your output is in %out_grid%.
&type

quit

&return

/*-----routines-----

/* Kill the output grids for focal mean and standard deviation
/*
&routine killms
  kill %out_mean% all
  kill %out_stdv% all
&return

/* Exit from an error condition.
/*
&routine exit
  &type ERROR encountered in randsamp.aml: Bailing out
&stop

```

```

/* PROBCCLASS.AML
/* Frank L. Dougher
/*
Mar. 10, 2002

&args in_root out_root

grid

/*&sv class1mask = [SCRATCHNAME]
/*&sv class2mask = [SCRATCHNAME]
/*&sv class3mask = [SCRATCHNAME]

&sv class1mask = %out_root%1
&sv class2mask = %out_root%2
&sv class3mask = %out_root%3

&sv count = 1
&do &while %count% <= 100
  &sv countstring = %count%
  &if %count% <= 99 &then &sv countstring = 0%countstring%
  &if %count% <= 9 &then &sv countstring = 0%countstring%
  &if %count% = 1 &then &do
    %class1mask% = con(%in_root%%countstring% == 1, 1, 0)
    %class2mask% = con(%in_root%%countstring% == 2, 1, 0)
    %class3mask% = con(%in_root%%countstring% == 3, 1, 0)
  &end
  &else &do
    &sv junkmask = [SCRATCHNAME]
    rename %class1mask% %junkmask%
    %class1mask% = (%junkmask% + con(%in_root%%countstring% == 1, 1, 0))
    kill %junkmask% all
    rename %class2mask% %junkmask%
    %class2mask% = (%junkmask% + con(%in_root%%countstring% == 2, 1, 0))
    kill %junkmask% all
    rename %class3mask% %junkmask%
    %class3mask% = (%junkmask% + con(%in_root%%countstring% == 3, 1, 0))
    kill %junkmask% all
  &end
  &sv count = %count% + 1
&end
/*****

DOCELL
  if (%class1mask% > %class2mask% & %class1mask% > %class3mask%)
%out_root%p = %class1mask%
  else if (%class3mask% > %class2mask% & %class3mask% > %class1mask%)
%out_root%p = %class3mask%
  else %out_root%p = %class2mask%
END
DOCELL
  if (%class1mask% > %class2mask% & %class1mask% > %class3mask%)
%out_root%c = 1
  else if (%class3mask% > %class2mask% & %class3mask% >= %class1mask%)
%out_root%c = 3
  else %out_root%c = 2
END

&return

```